KTH Industrial Engineering and Management

Geo-spatial electricity demand assessment & hybrid off-grid solutions to support electrification efforts using OnSSET: the case study of Tanzania

Babak Khavari

Andreas Sahlberg

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School of Industrial Engineering and Management
Energy technology EGI_2017-0093-MSC EKV1215
Division of Energy System Analysis
SE-100 44 STOCKHOLM

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Approved	Examiner	Supervisors
	Mark Howells	Alexandros Korkovelos Dimitris Mentis
	Commissioner	Contact person

Abstract

Increased access to modern energy fuels, especially electricity, is of high importance in order to promote sustainable development in developing countries. High quality planning processes using well developed energy models are required for globally increased electrification rates. The Open Source Spatial Electrification Tool (OnSSET) may be used for such purposes as it can model least cost electrification strategies in a region based both on increased grid-connection rates as well as off-grid electricity generation technologies. In this thesis some new developments to the methodology behind OnSSET have been studied. The first task was to add a new method of estimating residential electricity demand using remote sensing data. The second task was to add hybrid energy systems to the list of electricity generation technologies in OnSSET. The additions were also examined by means of a least cost electrification case study of Tanzania.

Strong correlations were found between residential electricity demand and GDP, electricity price and nighttime lights. One of these correlations was used to propose a new iterative method for setting residential electricity access targets in OnSSET. Some problems with the usability of NTL were discussed, and further research was proposed to examine the universality of the residential electricity demand correlations. Furthermore two mini-grid hybrid energy systems were developed for inclusion in OnSSET. PV-diesel hybrid systems were found to be cost-competitive with the already existing mini-grid technologies, while wind-diesel systems were found to be more expensive. It was discussed that the option of another method of choosing technology in OnSSET which includes more factors than simply LCOE may better capture the benefits of hybrid energy systems and allow for more diverse analyses. Finally it was found that a combination of grid-connection and off-grid technologies may be the most economic choice to reach 100% electrification rate in Tanzania for a cost between 2 and 55 billion USD depending on the level of electricity access target and choice of discount rate. PV technologies were found to be the dominating off-grid technologies in most cases.

Sammanfattning

Ökad tillgång till moderna energislag, inte minst elektricitet, är viktigt för främjandet av hållbar utveckling i utvecklingsländer. För att öka tillgången till elektricitet på en global nivå krävs det högkvalitativa planeringsprocesser som använder välutvecklade energimodeller. Energimodellen Open Source Spatial Electrification Tool (OnSSET) kan användas för detta ändamål då den kan användas för att beräkna den mest kostnadseffektiva strategin för att öka elektrifieringsgraden i en region baserat på ökad anslutning till det nationella elnätet kombinerat med fristående off-grid teknologier. I denna avhandling har två nya tillägg för OnSSET studerats. Det första syftet var att med hjälp av fjärranalyserad data utveckla en metod för att uppskatta hushållskonsumtion av elektricitet. Det andra syftet var att lägga till hybrida elsystem till de sju nuvarande teknologikonfigurationerna i OnSSET. Resultaten av dessa tillägg studerades med hjälp av en fallstudie av Tanzania.

Starka korrelationer hittades mellan hushållens elkonsumtion och BNP, elpriset och mängden nattligt ljus. Ett av dessa samband användes för att föreslå en ny iterativ metod för att sätta mål gällande hushållens tillgång till elektricitet i OnSSET. Några problem gällande användandet av nattligt ljus diskuterades och fortsatt arbete föreslogs där man bland annat bör undersöka universaliteten av de korrelationer som upptäckts. Vidare utvecklades två modeller för hybrida mini-elnät som kan inkluderas i OnSSET. Hybrida sol-dieselsystem visade sig vara ekonomiskt konkurrenskraftiga med andra mini-elnätsteknologier medan hybrida vind-dieselsystem var signifikant dyrare. Det diskuterades att nya metoder för att välja elteknologier i OnSSET som inkluderar fler aspekter än endast priset per kWh bättre skulle kunna fånga nyttan av hybridsystem och även möjliggöra en större vidd av analyser med hjälp av OnSSET. Slutligen så påvisade fallstudien att en kombination av anslutning till det nationella elnätet kombinerat med off-grid teknologier tycks vara det mest ekonomiska alternativet för att öka elektrifieringsgraden i Tanzania till 100%. Detta för en kostnad på mellan 2 till 55 miljarder USD beroende på energimål och diskonteringsränta. Bland off-grid teknologierna var solteknologier det dominerande energislaget.

Acknowledgements

We would like to thank our supervisors Dimitris Mentis and Alexandros Korkovelos for their invaluable guidance and support, both for the thesis itself and also during other relating activities. We would also like to thank Professor Mark Howells for making the opportunity to work with this project possible. Finally we would also like to extend our gratitude to the National Bureau of Statistics in Tanzania for their help providing data for the project.

Division of labor

This thesis has been written by two students, Babak Khavari and Andreas Sahlberg, each with their own objective. Both students have worked with OnSSET and a case study of Tanzania. Babak's specific objective relates to geospatial electricity demand assessment while Andreas' objective relates to hybrid off-grid technologies. Chapter 3, 5.6.1, 5.7.2 and 6.2 are specific for Babak's research. Chapter 4, 5.6.2, 5.7.3 and 6.3 are specific for Andreas' research. The remaining chapters have been written in conjunction by both students.

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Definitions

Energy model	A simplified representation of a real energy system that can be used to process large amounts of information and perform system analyses [1]
Energy system	A process chain responsible for meeting the energy demand including all or some of the steps from primary energy resource extraction to final energy use [2]
Hybrid Energy System (HES)	An energy system utilizing two or more energy technologies [3]
Levelized cost of electricity (LCOE)	Defined as the ratio between the lifetime costs (investment, operation, maintenance and fuel costs) and the electricity generated. Can be used to compare economic feasibility of different technologies as it shows the present value of the cost of building and operating a power plant over its entire lifetime [4]
Mini-grid electricity system (MG)	A local electricity generation and distribution system operating in isolation from the national grid serving multiple customers [5]
Nighttime lights (NTL)	Night lights detectable from space by satellites [6]
Remote sensing data	Data that can be gathered without being at the physical location, e.g. by satellite [7]
Standalone electricity system (SA)	An electricity generation system serving a single customer [5], i.e. rooftop solar panels
Sustainable development	In this thesis following the definition as stated in the Brundtland Comission: “development that meets the needs of the present without compromising the ability of future generations to meet their own needs” [8]
USD	United States Dollar

1 Introduction

1.1 Energy for sustainable development

Access to modern energy sources is of high importance for sustainable development. A strong relationship between the level of energy access and the state of development of a country has been suggested in a variety of reports. In order for a country to develop in a way that is sustainable across different sectors the country needs adequate and reliable energy supply [9], [10]. A particular emphasis may be placed on electricity for residential energy consumption in developing countries. Electricity is often required for many household appliances such as refrigerators, TVs and cell-phones [11]. It may also be the most efficient source of lighting and thus extending productivity hours [12]. Despite efforts towards reaching global sustainability targets and realizing the importance of modern energy access to do so, 1.1 billion people around the world still did not have access to electricity as of 2015 [13].

The lack of modern energy supply is evident while examining the cooking facilities in rural regions of developing countries. Close to 2.7 billion people lack access to modern fuels for cooking and these people instead often rely on traditional biomass [14]. This affects many aspects of sustainability, especially the environmental and social issues. The collection of fuelwood leads to deforestation and combustion of organic material increases the amount of harmful particles in the atmosphere. Furthermore, the workload for collecting fuelwood is unevenly distributed between the genders and age groups [15]. Most of the work is being done by either women or children. Furthermore, the combustion of organic material indoors increases the risk of negative health effects and premature deaths due to incomplete combustion [10]. This further highlights the importance of access to modern and reliable energy sources.

In September of 2015 the United Nations introduced 17 sustainable development goals (SDGs) to promote sustainable progress in developing countries. These goals are part of the 2030 Agenda for Sustainable Development targeted to be met during a span of 15 years. The scope is on a national level and the targets are designed to take different states of development for different countries into account. One of the most important ones is the 7th goal which is to supply people with sustainable, affordable, modern and reliable access to energy [16].

1.2 Energy planning

Energy planning in developing countries is vital in order to increase global access to electricity. An energy system must have the ability to supply enough energy to meet the current and future demand [17]. Energy systems require large investments and power plants may have both long life- and construction times, which means that decisions that are taken will affect the system for a long term. This calls for a thorough planning of energy systems [18]. An energy system should aim at being sustainable from an economic, environmental and social point of view [19]. A properly conducted energy planning process can help guide decision makers towards the most robust outcome possible.

1.3 Energy models and the geospatial dimension of energy planning

In the process of energy planning the use of energy models can be applied to answer questions and provide valuable insights. Computer models can process large amounts of data in order to generate demand forecasts, analyze energy supply strategies and impacts of energy policies etc. Mentis et al. also highlight the importance of the geo-spatial dimension in energy planning by integration of a Geographical Information System (GIS) in the energy modeling. In their paper they mention the fact that energy planning always has a linkage to geographical characteristics of the area in which the planning is being conducted. As national statistics are often incomplete or lacking in many areas relating to energy planning in developing countries GIS data may also be used to help filling these data gaps. Furthermore the ability to differentiate location specificities as well as visualization is also brought up as advantages of geo-spatial tools in energy planning [20].

There are many examples of the use of GIS tools for different aspects of energy planning. GIS has for example been used for renewable energy resource assessments on both national [21], [22], [20], [23] and continental [24] scales. Additionally GIS has been used to decide on the optimal location and size of bio-power plants [25], [26] and solar photovoltaics (PV) farms [27], [26].

Many renewable energy technologies are land intensive, meaning that they require large land areas. In many cases these technologies compete with one another and therefore it might be useful to know which one is more feasible. Calvert and Mabee used GIS-tools to compare different implications of using land for solar PV farms or biomass production in Ontario, Canada. Different areas were examined in order to assess which locations were suitable for each technology and in the cases where both technologies could be used the trade-offs for using each technology were examined [26].

Aydin et al. expressed the usefulness of GIS when selecting appropriate sites for renewable energy technologies including economic and ecological aspects. They used GIS-tools in order to identify areas in western Turkey best suitable for wind-PV hybrid systems. By first identifying areas where wind power and solar PV systems are viable options and then combining this information the areas best suited for wind-PV hybrid systems were chosen [23].

One particular field where GIS systems may be of importance is that of improved energy access strategies in developing countries. In many developing countries mini-grid and standalone power systems may play an important role for increasing the electrification rate [28]. This is especially true for remote areas and areas with e.g. low population density and for low electricity access targets [18]. In these cases the investment required for extending the national grid might not be economically justifiable compared to installing off-grid systems. Most often a combination of grid-connection and off-grid systems may be the best option for a developing country to reach universal electrification as rapidly and economically as possible.

Many traditional energy models such as MARKAL, TIMES, MESSAGE etc. can be used for energy modeling and optimization of the power system. However these systems generally focus on analyzing the mix of grid-connected power plants. In order to also consider where on- or off-grid technologies should be used it is important to take into account geospatial information regarding population distribution, resource availability, distance to the current infrastructure etc. Therefore a new type of energy model that incorporates GIS tools may be used for this sort of analysis.

Currently there are few models for electrification planning that utilize GIS tools to compare on- and off-grid technologies known to the authors. Network Planner[1] is one such program which compares grid-connection, diesel generation and standalone photovoltaic (PV) systems for specified locations. The program uses GIS to calculate the shortest distance for grid extension to multiple areas [29]. GEOSIM[2] is another GIS based program which determines the optimal electrification option for areas which may function as centers for social and economic development. GEOSIM also identifies which areas can be connected to the grid based on economics and grid capacity, and compares several other technologies for the other areas [29]. Lastly, the Open Source Spatial Electrification Tool (OnSSET) uses GIS to compare the least-cost electrification strategy in an area based on grid-connection and six different configurations of off-grid technologies [30]. OnSSET differs from the previous tools in two important ways. First of all, it considers all areas of a country or region instead of focusing on certain locations. Secondly, the OnSSET code is open source allowing anyone to use and customize the tool. A further description of OnSSET is given in Chapter 2.

1.4 Statement of objectives

OnSSET currently determines which households are currently likely to be electrified or unelectrified based on a set of conditions. However no distinction is made between the levels of electricity access for the electrified households. Additionally two uniform electricity access targets are specified in the program for all urban and all rural households. The first objective of the thesis is to investigate remote sensing data and geospatial determinants of household electricity consumption, with a particular focus on satellite detectable nighttime lights (NTL). This may provide more detailed insights of residential electricity consumption and can possibly be used to differentiate the electricity access targets in a more realistic.

The second objective of the thesis is to develop a method to consider hybrid electrification options in geospatial electrification planning. The off-grid technology configurations currently included in OnSSET are each based on a single fuel. Hybrid technologies may potentially overcome problems

[1] Available at http://optimus.modilabs.org
[2] Available at http://www.geosim.fr

that can be associated with each technology if operating by itself and therefore be more reliable. By adding the ability to locate areas where hybrid technologies are competitive a more reliable energy plan may be proposed.

Furthermore the results of the first two tasks are implemented in an OnSSET case study of Tanzania to find the least-cost electrification strategies for the country. The new additions are examined to analyze the effects they may have for future energy planning studies using OnSSET.

1.5 Methodology

The methodology in this thesis follows three main steps. First an in depth literature review on the state of the art for the respective tasks, i.e. remote sensing of electricity consumption and hybrid systems modeling, is conducted. Secondly, based on the knowledge acquired from the literature study the relevant methods and calculations are identified and integrated in OnSSET. This step includes both the enhancement of the OnSSET code and the GIS routines. Lastly a case study of Tanzania is conducted using OnSSET with the new additions. Chapter 2 presents a basic description of the existing version of OnSSET. Chapter 3 and Chapter 4 describe the development of the new methods for identifying household electricity consumption and modeling hybrid systems respectively. The case study and results are presented in Chapter 5. Finally the discussion and conclusions are given in Chapter 6 and Chapter 7.

2 The Open Source Spatial Electrification Tool

OnSSET is an open source tool which can be used to determine the split between generation technologies to provide least-cost electrification option in a country or region. OnSSET is written in Python and draws on the advantages of GIS. The study-area is divided into a mesh of square grid-cells usually ranging between 1 and 100 km^2. The least-cost technology configuration is calculated for each cell based on the levelized cost of electricity (LCOE) which allows for easy comparison of technologies over their lifetime from a purely economic perspective. Apart from the technology splits and LCOE in each cell, the program also calculates the total investment costs required and the number of new people to receive electricity by each technology. The current version of the tool considers seven configurations of generation technologies divided into three categories as seen in Table 1; grid-connection (GC), mini-grid (MG) and stand-alone (SA). A further description of the methods and calculations behind the OnSSET code is given below.

Table 1. Electricity generation technologies considered in OnSSET

Category	Technology
Grid-connection	National grid
Mini-grid (MG)	Solar PV
	Hydro
	Wind
	Diesel
Stand-Alone (SA)	Solar PV
	Diesel

2.1 Demand assessment and base-year electrification status

The energy demand is estimated based on demographics and residential energy access targets. The population density in each cell given by a GIS dataset is calibrated so that the total population matches the official statistics for the base year. The cells are then assigned an urban or rural status based on the population density to reflect the urban ratio in the base year. The population density in the final year is calculated based on projected growth rates for the urban and rural population respectively. Finally, the electricity access targets for urban and rural population are multiplied with the population in each cell to give the total electricity demand.

The cells which are considered to be grid-connected initially are identified and calibrated based on the base year electrification rate. The calibration calculates the minimum NTL and population density and maximum distance to roads and the grid to determine which cells are electrified to reflect the current electrification rate.

2.1.1 Electrification tiers

The electrification algorithm in OnSSET may use the electrification tiers from the Global Tracking Framework (GTF) report for electricity access targets. In the GTF report a new multi-tier approach for energy access was introduced as replacement for the prior binary measure, which describes only if a household is electrified or not. In the case of electricity the binary method was not able to assess whether an electricity connection provided sufficient services or not. Furthermore, the binary method is limited because its definition of electricity access is centered on whether the household is connected to the grid or not. The multi-tier approach uses various methods to present the electricity supply in several dimensions and also captures the use of these electricity services with a multi-tier framework [31].

The multi-tier approach is based on residential electricity consumption and describes if the household has access to electricity as well as the level of access. The multi-tier approach measures two closely related categories, namely electricity supply and electricity service. The electricity supply is divided into five different tiers for electrified households and defined on the basis of certain attributes describing supply such as quantity of electricity, reliability, duration etc. As the supply tier number increases, different electricity services become available and feasible. The electricity service category is divided into five tiers as well and is focused on the ownership of different appliances [31]. Table 2 and Table 3 below depict the multi-tier matrix of household electricity access and the multi-tier matrix of household electricity services respectively [32].

Table 2. Multi-tier matrix of household electricity access

		Tier 1	Tier 2	Tier 3	Tier 4	Tier 5
Peak capacity	Power capacity (W)	Min 3 W	Min 50 W	Min 200 W	Min 800 W	Min 2 kW
	Power capacity (Wh)	Min 12 Wh	Min 200 Wh	Min 1 kWh	Min 3.4 kWh	Min 8.2 kWh
Availability (duration)	Hours/day	Min 4 hrs	Min 4 hrs	Min 8 hrs	Min 16 hrs	Min 23 hrs
	Hours/evening	Min 1 hr	Min 2 hrs	Min 3 hrs	Min 4 hrs	Min 4 hrs
Reliability					Max 14 hrs disruption/week	Max 3 hrs disruption/week

Table 3. Multi-tier matrix of household electricity services

	Tier 1	Tier 2	Tier 3	Tier 4	Tier 5
Tier criteria	Task lighting and phone charging	General lighting and phone charging and television and fan	Tier 2 and any medium-power appliances	Tier 3 and any high-power appliances	Tier 2 and any very high-power appliances

2.2 Off-grid technology LCOE

The LCOE for off grid technologies is calculated from the unit investment cost, energy demand and energy resource availability or fuels costs depending on technology. All of these factors except the first are varying spatially. The formula used for calculating the LCOE is given by Equation 1 [18]:

$$LCOE = \frac{\sum_{t=1}^{n} \frac{I_t + O\&M_t + F_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1+r)^t}} \qquad (1)$$

Where t is the year, I (USD) the investment cost, O&M (USD) the operation and maintenance cost, F (USD) the fuel cost, E (kWh) the energy generation and r the discount rate.

2.2.1 Energy resource availability

For the renewable energy generation technologies the energy resource availability is required, i.e. the solar global horizontal irradiation (GHI), average wind speed and hydropower potential, to estimate the capacity factor and subsequently the necessary capacity installments. The required capacity is calculated based on the peak demand divided by the capacity factor.

2.2.2 Fuel cost

The only off-grid technologies that currently include fuel costs are MG and SA diesel, the other technologies utilize renewable energy resources. The fuel cost varies spatially and depends on two factors; the diesel pump price per liter in the country which is considered to be uniform for the whole country and the additional transportation cost which varies depending on the distance to large cities[3]. The cost of diesel, P_t (USD/kWh) in each cell is given by Equation 2:

$$P_t = 2 * \frac{P_d * c * t}{V} * \frac{1}{LHV_d} \qquad (2)$$

Where P_d (USD/liter) is the diesel pump price, c is the diesel consumption of the diesel delivery truck (l/h), t (h) is the transport time from large cities, V (l) is the volume of diesel transported and LHV_d (kWh/l) is the lower heating value of diesel[4] [33]. The factor 2 is due to the delivery truck driving both back and forth to deliver the diesel.

2.2.3 Mini-grid cost

The MG technologies differ from the SA technologies in the fact that they add a cost for the distribution network that needs to be built. The shortest length of the grid network that is

[3] In this thesis large cities are defined as cities with a population larger than 50 000 people

[4] The default values of the model are; LHV_d = 9.944 kWh/l, V = 300 l for SA systems and V = 15 000 l for MG systems, c = 14 l/h for SA systems and c = 33.7 l/h for MG systems.

necessary is determined mainly based on the grid-cell area, population density and peak power demand. The structure of the network is further described in [34] and the cost of the power lines is added to the investment cost in Equation 1.

2.3 Grid electrification algorithm

The grid-connection option is compared to the off-grid technology configurations using an iterative algorithm. A reference matrix is derived where the minimum population density required making grid-connection more affordable than off-grid technologies is determined based on the distance to the current and planned grid. The distances used in the matrix are multiples of the cell-sizes. Each cell is then compared to the reference matrix. If the population density is larger than the minimum population density required according to the reference matrix for the distance, then the cell is considered to be grid-connected. When all cells have been examined the distances to the grid network for un-connected cells are updated, and the process is repeated until no more cells are connected. The maximum grid-extension length considered is 50 km based on techno-economic considerations [35].

3 Geo-spatial demand assessment

3.1 Introduction

The aim of this chapter is to propose an alternative way of determining the electricity consumption using remotely sensed data. This could allow for an improved way of estimating the electricity demand in OnSSET compared to the current method where a uniform target is specified for urban and rural areas. There are many examples in the literature where remote sensing data and other factors have been used to describe electricity demand or consumption.

One of the remote sensing datasets that has been used to determine electricity access as well as electricity consumption is nighttime lights. NTL is satellite imagery of the earth taken at night showing the areas of the planet where there is light at night. The lights detected on these maps are mostly anthropogenic and hence represent locations with human settlements and other human activities. The relationships between NTL and electricity access as well as electricity consumption have been studied in a large number of papers [36]-[42]. Most of these papers are either on a national or regional level. There are few studies that assess this relationship in rural areas of developing countries or on the basis of a high spatial resolution.

Doll and Pachauri used the nighttime light data in combination with a population map and a map visualizing urban extent. With these maps the proportion of the population living without electricity was determined on a global scale and compared to the national statistics for different countries. The authors concluded the nighttime light data difficult to use over urban areas due to the sensitivity of the sensor and instead chose to focus on electricity access in rural areas. The results of the study show that the analysis of NTL gives an overestimation of population without access to electricity compared to the available statistics in all regions except for South Asia. The authors expressed that the correlation could have been better if it were not for some limitations in the datasets used. Two of the most prominent shortcomings of the data that they mentioned are the fact that nighttime light data is best suited for detection of outdoor lighting and that the density of electricity consumption in rural areas is not large enough to be picked up by the satellite [36].

Kiran Chand et al. used NTL to estimate the changes in electrical power consumption across India between 1993 and 2002. The stable light images of three of these years have been used to assess the change in nighttime light over India. They found that increasing electricity consumption gives rise to a larger number of lit pixels in the country. The same trend could be seen when the population was compared to nighttime light. The authors concluded that data on nighttime light was well suited for determination of electricity consumption across India as well as for determination of socio-economic development over time [38].

Min et al. used NTL in order to detect rural areas in Mali and Senegal with electricity access. This was the first ground-based validation of the U.S. Air Force Defense Meteorological Satellite Program - Operational Linescan System (DMSP-OLS) nighttime lights. The purpose of the report was to assess the reliability of the DMSP-OLS dataset for detection of electricity consumption in rural areas of developing countries. In order to do this the imagery from the DMSP-OLS satellite was compared to surveyed data. The surveys collected data regarding electrified and non-electrified villages in both countries which were pinpointed on NTL maps with the help of GPS-coordinates. The results show that villages with electricity consumption can be detected using NTL and that electrified villages have a higher light output than non-electrified villages even at very low consumption levels. The conclusion is somewhat close to the one proposed by Doll and Pachauri; the electrified villages are brighter because of streetlights and the correlation with household consumption is weak [41].

Furthermore, Min together with Development Seed and The World Bank has conducted The India Lights project[5]. In their project they have used data collected by the DMSP-OLS satellites between the years of 1993 and 2013 in order to assess the change in luminosity for 600 000 villages across India during this period [43].

Other authors have examined the relation between economic factors and electricity consumption. The literature diverges concerning the relationship between economy and electricity demand and consumption. Some papers suggest a uni-directional relationship where higher income leads to higher electricity consumption but not the other way around [44], [45]. Other papers suggest that the causality runs in the opposite direction [46]-[48] or a bi-directional relationship [49], [50]. The differences between these are important. A causality going from economic growth to electricity means that a governing institution can introduce policies to reduce electricity consumption without having any effect on the economic structure of the system. An opposite causality could mean that lowering electricity consumption might lead to hampered growth [51].

Wolde-Rufael tested the causality between electricity consumption per capita and the real Gross Domestic Product (GDP) for 17 African countries. The analysis focused on the time span of 1971 to 2001. Out of the 17 countries, five did not show causality between economic growth and electricity consumption at all. Six countries showed causality in the direction of economic growth to electricity consumption, three in the opposite direction and three showed a bi-directional causality. The paper shows that historical economic growth for some countries can serve as an indicator for present electricity consumption and that the opposite is true for some other countries. It was pointed out that the results should be considered with caution as the electricity consumption in these countries was low and usually concentrated around urban areas. Additionally the report only takes into account electricity supplied by the electrical grid [51]

A major reason why large parts of the developing world are lacking electricity access is shortage of economic resources. It can be expected that the purchasing power relating to electricity may be low in areas with high poverty levels. In the literature there are several studies on the relationship between poverty and the amount of electricity consumed [36], [52].

[5] Information regarding the project is available at: http://india.nightlights.io/#/nation/2006/12

Another important determinant of electricity consumption that is not necessarily available in the form of geo-spatial data sets is the price of electricity. The correlation between electricity price and electricity consumption is well documented. In a perfect market the consumer will buy electricity until the marginal profit is lower than the marginal cost. The producers will act in a similar fashion by producing electricity until the marginal cost of producing a unit is higher than the price of selling that same unit. In reality a perfect market is very unusual since it requires the customers to have access to an unlimited amount of information regarding the market. Instead customers act based on a limited amount of information and cognitive ability. Even with these limitations customers tend to follow the principle of lowering their consumption as the price increases. In the literature there are several papers describing the price elasticity of electricity consumption [53]-[59].

Inglesi-Lotz examined the price elasticity of electricity in South Africa through the years of 1980 to 2005. In the paper it is pointed out that changes in electricity price is the most important factor for changes in electricity demand. The value added to the field by this paper is the introduction of a changing elasticity as the previous studies have all assumed a constant elasticity between price and electricity through the time periods observed. The analysis found a large elasticity during the late 80s but since 1991 the elasticity fell considerably and in 2005 the electricity demand could be considered inelastic to price changes. One important conclusion from the paper is that the price elasticity is higher if the price is higher [58].

3.2 Methodology

To establish a relationship between electricity consumption and remote sensing data several datasets that may potentially relate to electricity consumption were collected. Each dataset comes in raster format and relatively high spatial resolution. The high resolutions of the datasets enable subnational analysis. These datasets were then compared to data from the Household Budget Survey (HBS) of 2011-2012 which was conducted and published by the National Bureau of Statistics (NBS).

In the survey the households answered a set of questionnaires accompanied with a diary. In the diary the amount of electricity purchased as well as the price paid for the electricity was recorded daily during 28 days. Due to reasons of confidentiality the exact location of each household is not given in the data, but only which ward they are located in. A ward is a small administrative area and a map displaying the 2 805 wards in Tanzania can be seen in Figure 1. The total electricity consumption registered in the diaries in each ward has been divided by the total number of household members in the surveyed households in the ward to give the electricity consumption per capita. This electricity per capita was then multiplied with the total population in respective ward generated from the GIS data to find the total electricity consumption representative for the ward. To calculate the electricity price used in this chapter the total electricity in each ward was divided by the total amount paid in said ward according to the collected survey data. This electricity price is assumed to be the average price of electricity in the ward.

The GIS datasets used in the analysis were processed with ArcGIS to produce statistics for each ward. These statistics and the statistics based on the NTL were then analyzed using StatPlus, both at the ward and household level. The analysis was performed using linear regression models to find correlations among the electricity consumption and other data. Every dataset was first tested against the electricity consumption on its own and then in combination with other variables. A more in depth description of the NTL and other datasets follows below.

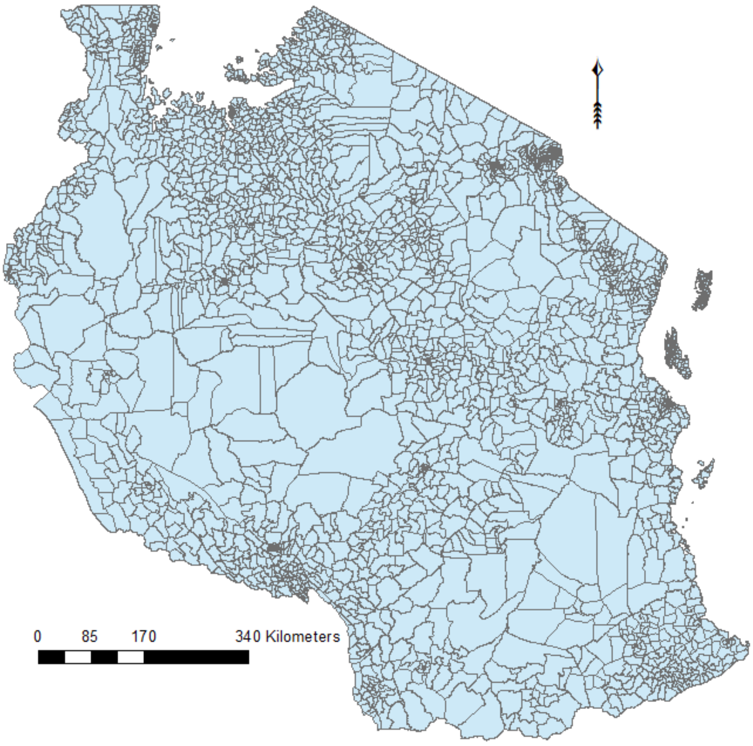

Figure 1. Map of wards in Tanzania based on [60]

3.2.1 NBS survey

The National Bureau of Statistics in Tanzania has conducted several household surveys. For the purpose of this paper the NTL of 2011-2012 has been used. The survey was carried out between the 1st of October 2011 and October 12th 2012. This survey was the sixth installment of reports that have been carried out in order to assess the success of the National Strategy for Growth and Reduction of Poverty. The main objective of this survey was to give estimates regarding household's economic activities such as incomes and expenditures. The analysis focused on indicators relevant for poverty measurements. There are three previous household budget surveys, one for the years of 1991-1992, one for 2000-2001 and one for 2007. The way the surveys are designed allows some of the parameters to be compared so as to examine how they have developed through time.

A total number of 10 400 households spread across the country were chosen for interview. The response rate of the survey was 94.1 % and in order to increase the number of households, 398 additional households were added to the sample, resulting in a total of 10 186 households. Of these, around 550 reported some level of electricity purchases. Approximately three quarters of the population surveyed was situated in rural areas. The households were visited and interviewed once initially, thereafter the households were visited regularly over the coming 28 days in order to fill in a diary and to answer additional questionnaires. In the diary the household members fill in all household transactions i.e. expenditure and consumption [61].

3.2.2 Datasets

Table 4 below lists the datasets that were used in this chapter. A more detailed description of some of these datasets follows in the sub-sections below.

Table 4. Datasets used in the analysis

Dataset	Resolution	Source
Administrative boundaries (2002)	Polygon	[60]
NTL (2012)	1 km × 1 km	[62]
Population (2013)	100 m × 100 m	[63]
GDP (2010)	1 km × 1 km	[64]
Poverty (2013)	1 km × 1 km	[65]
Transmission lines (2015)	Polylines	[66]
Travel time (2008)	1 km × 1 km	[67]
Roads (2015)	Polylines	[68]

3.2.2.1 Nighttime lights

For the purpose of this thesis the DMSP-OLS NTL data has been used. Each point in the dataset is represented by a digital number between 0 and 63 depending on the brightness of that pixel. The value 0 represents areas with no visible light while all pixels at or above the maximum detectable range of the sensor are considered to be saturated and receive the value 63 [69]. The saturated pixels hence may not give a fair representation of the actual brightness in that pixel. The problem of oversaturation is most common in city centers and other areas with high population densities.

The data has been collected by different generations of satellites since 1972 [70]. Public maps of the NTL are available for each year between 1992 and 2013 [71]. For this study the maps of 2012 has been used since this was the year of the NBS survey. For the latter years there are three maps for each year and satellite. The first map displays the number of cloud-free observations in each grid cell. The second map displays the average value of each cell without any filters applied. The second map is cleaned to produce the third map which shows only consistently visible lights and is called the stable lights map.

The NTL data that was deemed most useful for this analysis is the stable light image. For the purpose of this study the sum of nighttime light and nighttime light per square kilometer have been studied in each ward. The problem that might occur as a consequence of filtering out the noise in the stable light map is bottom-censoring. Bottom-censoring in this case means that some low-level emitting pixels that are supposed to have non-zero values are given the value zero because they are being mistaken as temporary light sources [72], [73]. This can be seen in the data studied. In the nighttime light maps for 2012 there are no non-zero values below three globally and no non-zero values below five in Tanzania.

This leads to uncertainties regarding which pixels actually have a value of zero and the pixels that are wrongfully censored. The issue of bottom-censoring combined with these maps possibly being better suited for detection of outdoor lighting than residential electricity consumption may affect the analysis. Adding to the problem is also the fact that many of the households surveyed by the NBS were situated in rural areas, meaning their electricity consumption might be too low to be detected by the satellites.

In 2014 the DMSP-OLS map was replaced by a newer generation of satellite called Visible Infrared Imaging Radiometer Suite (VIIRS). This satellite has a higher resolution than the DMSP-OLS satellite and can therefore give more precise measurements of light sources. Apart from different resolutions another difference between the satellites is the data acquisition time. The DMSP-OLS satellite collects data at approximately 9 p.m. while the VIIRS satellite collects data around 1.30 a.m. The DMSP-OLS has been chosen due to the period of data acquisition coinciding with the NBS survey and because one could argue that most residential light sources are switched off at 1.30 a.m. and therefore not visible on VIIRS imagery. For future studies it might be interesting to compare the two different datasets in order to determine the amount of luminance coming from residential electricity use. However, this would likely require additional information since the scale of the DMSP-OLS satellite is relative and depending on the gain settings of the sensors, which is constantly adjusted [43].

3.2.2.2 GDP

There are several previous studies visualizing the spatial characteristics of economic activity using nighttime light data and the results from many of these studies have been close to the official statistics [72], [74], [75]. Gosh et al. have developed a method to estimate subnational GDP with a resolution of 1 km^2 and subsequently produced a global map for GDP (Figure 2). The map takes into account both formal and informal GDP. In order to create the map Gosh et al. used data regarding NTL (DMSP-OLS), population, official GDP statistics and the contribution of the agricultural sector to the GDP. The latter is important since agricultural contribution is not taken into account in the DMSP-OLS maps because the electricity in this sector is most commonly used for purposes other than lighting [64].

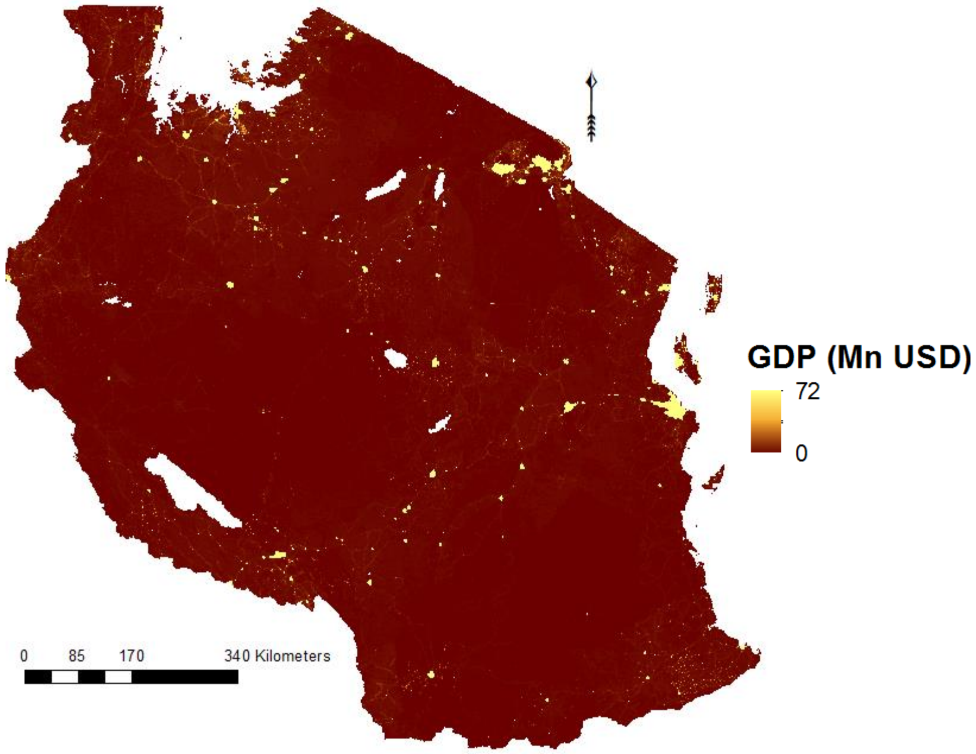

Figure 2. GDP in million USD, based on data from [49]

For the purpose of this paper the total GDP in million USD in each ward as well as the GDP per square kilometer in million USD for each ward has been aggregated from the map of Gosh et al.

3.2.2.3 Population

The population map has been used in order to evaluate the population density in different areas. The population map used in this thesis depicts the population in 2010.

3.2.2.4 Poverty

Three different datasets for poverty have been used. All of them were based on the year of 2010. The first map shows the proportion of the poor population as defined by the Multidimensional Poverty Index, while the second and third maps show the proportion of the population living below 2 and 1.25 USD per day respectively. The poverty maps have been used to assess the number of people who live above these thresholds given in each map in every ward.

3.2.2.5 Travel time

The travel time map shows the time it takes from each grid cell to the closest city with more than 50 000 inhabitants. This dataset was used to assess how remote the households were located. Since the travel time differs in different areas of a ward the average travel time in each ward has been used.

3.3 Results

All of the variables and datasets introduced in section 3.2.2 have been tested in different combinations against the total electricity consumption and the electricity consumption per household. In this section the results which are deemed statistically significant are presented. This means that the R-squared value of the regression line should be high. The R-squared value or coefficient of determination is an indicator of how well a variable fits an ordinary regression line. R-squared is defined as the percentage of observations of a dependent variable that can be explained by a linear model. The value of R-squared is between 1 and 0 and the larger the value is the better.

The analysis showed no robust relationship between electricity consumption and the distance to the existing grid or road distance. This can be seen in Table 5.

Table 5. Regression lines with saturated pixels and bottom-censored wards removed.
$*p < 0.1$ $**p < 0.05$, $***p < 0.01$. Robust standard error in parentheses

Dependent Variable:	**OLS regression**	
log(total electricity)	(1)	(2)
log(Distance to transmission network)	3.115*** (0.3826)	
log(Distance to road)		-0.08 (1.6034)
Number of observations	72	72
R-squared	0.47	$3.94 \cdot 10^{-5}$

Furthermore the relationship between the amount of residential electricity consumption and the sum of nighttime light by itself is rather weak when all the wards from the NTL were included. This is in line with some reports, but contradicts others. Since there are different claims regarding the usefulness of NTL in assessing residential electricity consumption, an examination of the difference in the amount of NTL between electrified and non-electrified wards in Tanzania has been conducted (Table 6).

For the purpose of determining whether this difference is significant the t-statistics have been used. The t-statistics is useful when analyzing the difference between population means. In this case the average nighttime light in wards with and without electricity purchases recorded in household diaries have been compared. As can be seen in Table 6 the t-statistic is rather large and indicates that there is a significant difference between the amount of NTL in wards with and without electricity. This is consistent with previous studies that claim there is a relationship between the existence of NTL and access to electricity. However, it is possible that that the nighttime light comes from streetlights rather than residential electricity use.

Table 6. Comparison of wards with and without nighttime light

	Electrified	Non-electrified
Sample size	137	191
NTL mean	24.75	3.47
Standard deviation	26.06	10.04
t-stat: 9.08		

3.3.1 Total electricity in ward

As explained above the analysis yields no significant relationship between the NTL light data and the electricity consumption unless certain conditions were imposed. At first the wards with saturated pixels were excluded while keeping the wards with zero NTL. In this case there were some variables that could describe the electricity consumption sufficiently enough on their own using linear regression lines with logarithmic values. Table 7 shows five different linear regression lines; one with GDP, three with different measures of poverty and one with travel time. The dependent variable is the logarithm of total electricity consumption which is the amount of electricity that the population in each ward can be expected to purchase yearly. There were however no combination of two or more variables in this case that gave a robust relationship describing the total electricity consumption with all variables having a significance level better than 10%.

*Table 7. Regression lines with saturated pixels removed. ***p<0.01. Robust standard error in parentheses*

Dependent Variable: log(total electricity)	OLS regression				
	(1)	(2)	(3)	(4)	(5)
log(GDP)	1.3781*** (0.0354)				
log(Population with more than 2 USD/day)		1.3999*** (0.0244)			
log(Population with more than 1.25 USD/day)			1.2866*** (0.0235)		
log(non-poor population according to MPI)				1.2086*** (0,0216)	
log(Travel time)					2.422*** (0.1358)
Number of observations	95	95	95	95	95
R-squared	0.94	0.97	0.97	0.97	0.77

In the second step to overcome the problems of oversaturation and bottom-censoring and trying to find correlations including more than one variable an analysis excluding the wards with saturated pixels or with a sum of NTL equal to zero was performed. When using the downsized data it was found that NTL, GDP and travel time are well correlated with the electricity consumption on a ward level using linear regression models with logarithmic values. Table 8 shows three models describing the electricity consumption. The first model takes into account only the sum of NTL while the second and third models add the sum of GDP (USD) in the wards and the average travel time respectively.

*Table 8. Regression lines with saturated pixels and bottom-censored wards removed. *p < 0.1 **p < 0.05, ***p < 0.01. Robust standard error in parentheses*

Dependent Variable: log(total electricity)	**OLS regression**		
	(1)	(2)	(3)
log(Sum of NTL)	2.139*** (0.0494)	0.5216** (0.2721)	0.4894** (0.2695)
log(GDP)		0.5130*** (0.0853)	0.5754*** (0.0922)
log(Travel time)			-0.2769* (0.1662)
Number of observations	72	72	72
R-squared	0.96	0.98	0.98

3.3.2 Electricity consumption per household

The previous correlations presented in this chapter are on the basis of wards. However, since OnSSET currently works with electricity access at household levels it is of interest to examine whether there are correlations between the studied datasets and residential electricity consumption. Different variables have been tested and a combination of the electricity price, sum of nighttime light and GDP was able to describe the monthly electricity consumption per household. As expected the amount of electricity in a household increases as the price of electricity decreases and NTL and GDP increases. Table 9 below shows the linear regression line describing the relationships between these variables and residential electricity consumption.

*Table 9. Regression lines for electricity consumption per household. **p<0.05, ***p<0.01. Robust standard error in parentheses*

Dependent Variable: log(electricity consumption per household)	**OLS**		
	(1)	(2)	(3)
log(Sum of NTL)	0.5612*** (0.0394)	1.0275*** (0.1)	0.7276*** (0.154)
log(Price of electricity)		-0.4671*** (0.0942)	-0.5667*** (0.0992)
log(GDP)			0.2781** (0.1113)
Number of observations	542	542	542
R-squared	0.74	0.81	0.82

In Table 10 a modified version of the relationships in Table 9 is presented. The monthly residential electricity consumption is described without the use of NTL. The nighttime light has been removed from these relations for two reasons. First of all because of the difficulty of projecting NTL into the future which affect the possibility of using the relationships for a future demand analysis in OnSSET. Secondly bottom-censoring and oversaturation are additional reasons for removing NTL. For this relationship all households which reported electricity consumption in the NTL were considered as independent observations, instead of summarizing them based on wards. This allowed for an increased number of observations and more detailed data for electricity price in each household. It was found that the monthly electricity consumption per household could be explained well using the electricity price and the GDP per area in the ward that the household was located in. This relationship is used in order to examine the level of electricity consumption different households can afford at different locations in a country in later parts of the thesis.

*Table 10. Regression line used for projection in OnSSET. ***p<0.01. Robust standard error in parentheses*

Dependent Variable:	**OLS**	
log(electricity consumption per household)	(1)	(2)
log(Price of electricity)	- 1.3590*** (0.0324)	- 0.9266*** (0.0339)
log(GDP/area)		0.4793*** (0.0254)
Number of observations	542	542
R - squared	0.76	0.86

3.4 Discussion and conclusion

From the analysis it was found that there were strong correlations between the total electricity consumption and GDP, NTL, travel time and the level of poverty on a ward level. There were no strong correlations when nighttime light was used on its own against the residential electricity consumption with the entire dataset present. However, when the dataset was downsized to exclude saturated or bottom-censored pixels, NTL contributed significantly to the correlation in combination with other variables. The fact that nighttime light data correlated to electricity consumption only when certain criteria were imposed may indicate that the NTL data need to be further improved in order to counter these problems. On a residential level there was a correlation between GDP, NTL and electricity price to electricity consumption. These results are in line with the literature claiming that there is a correlation between the amount of nighttime light and residential electricity consumption.

The analysis shows a significant difference in light emittance between electrified and non-electrified wards. This is likely due to wards with electrified households having access to electricity for commercial uses as well, such as street lighting.

It was found that the distance from the transmission network was not a solid determinant of the electricity consumption. This is a rather surprising result due to the fact that one would expect that the electricity consumption is larger in areas with existing infrastructure. The absence of correlation between these variables and the electricity consumption could be due to the exact locations of the households not being available or that the georeferenced transmission network is poor and therefore not representative. It can also be due to the fact that the connectivity rate in Tanzania is rather low and hence a considerable portion of the population with electricity access might not live in close proximity to the grid.

4 Hybrid energy systems

4.1 Introduction to hybrid systems

A hybrid energy system (HES) generates electricity by utilizing two or more energy sources. The combination of different energy generation technologies may draw from the strengths of the respective technology to improve system performance. The main advantage of hybrid systems is a higher reliability and more service hours compared to single technology systems, as well as decreased fuel usage compared to diesel systems [3]. Decreased use of fuel in diesel generators also brings environmental benefits due to reduced emissions [76]. Intermittent renewable technologies for example may be backed up by diesel generators or another dispatchable technology in order to reduce the risk of power shortages or to cover peak demand. Non-dispatchable technologies with different daily or seasonal generation curves may also be combined to produce a steady amount of electricity that neither technology could achieve by itself. Hybrid systems may also be more affordable and less sensitive to fuel costs.

4.2 State-of-the-art in hybrid systems modeling

There are multiple tools for modeling off-grid hybrid system available online. Some of the more well-known ones are HYBRID2 [77] and TRNSYS[6] which are simulation systems, and iHOGA[7] and HOMER[8] which are optimization systems. The last one is often considered to be the most commonly used software for hybrid system analysis [78].

These modeling tools generally require resource and techno-economical inputs in order to either analyze economic performance or optimize sizing of the system. Oftentimes the hybrid system is simulated over a period of time divided into time-steps of one hour or less [79]. The modeling tools available commonly examine the HES for a specific location, and do not cover larger areas as is required for the OnSSET tool.

4.3 Hybrid energy system components

A hybrid system can be configured in many ways, but some common components are found in most HES. For electricity generation one or more renewable energy sources are often used in combination with a diesel generator. Additionally a battery or other storage system can be used to balance the supply and demand. Furthermore a control system which decides which technology should supply the electricity in every moment is often used and a number of AC/DC inverters depending on the electricity supply technologies and the load. All of these components are not necessarily used for all hybrid systems. A PV/wind system for example might not include a diesel

[6] Available at http://www.trnsys.com/
[7] Available at https://ihoga-software.com/en/
[8] Available at http://www.homerenergy.com

generator or a PV/diesel system may not include storage. A simplified chart of a hybrid system can be seen in Figure 3 and the components are described in more detail below.

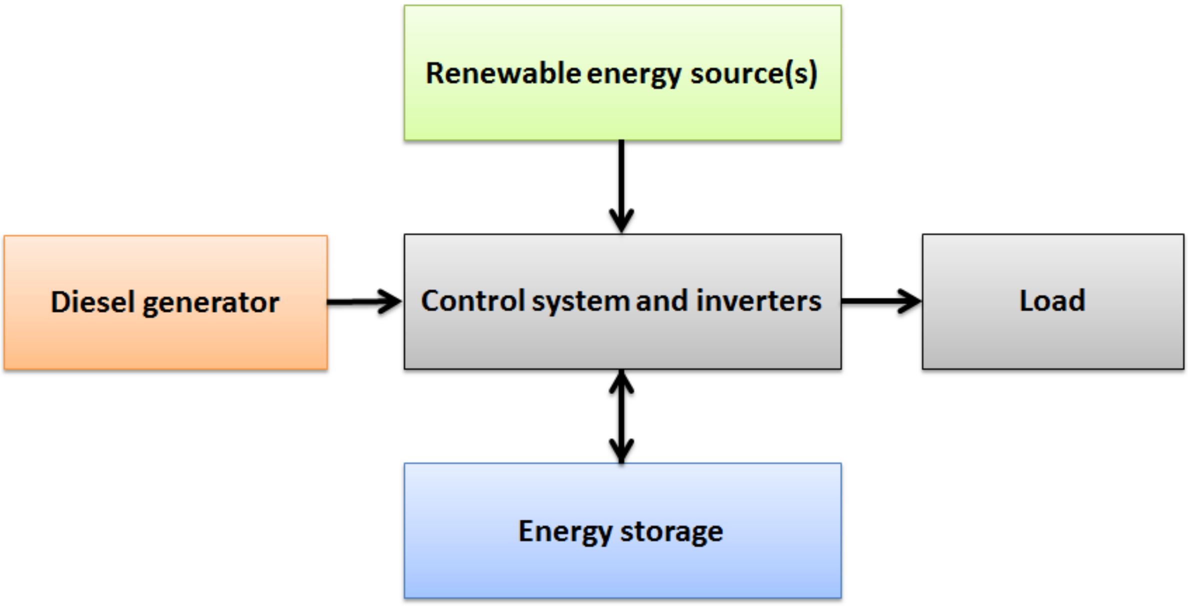

Figure 3. Hybrid renewable energy system, based on [80]

4.4 Method

Information regarding the functionality and mathematical modeling of the hybrid system components is gathered from literature. Other variables affecting the performance of the hybrid system such as renewable resources and load curves are examined. Using this information, all the pieces are combined to present models for two hybrid systems; a PV-diesel hybrid system and a wind-diesel hybrid system. The result presents the composition, dispatch strategy and method for use in OnSSET.

4.4.1 Load curves

In order to effectively plan an energy system the energy demand must be estimated first. The energy demand can be seen as a combination of two components; the total annual demand and the load profile. According to the International Energy Agency (IEA) a typical load curve in rural areas has a medium morning and midday load, a high evening peak and a low or non-existent load during the night. The load curve naturally changes depending on the type of appliances that are used. For low energy demand mainly used for indoor lighting almost all of the energy may be used during the evening hours. For more continuous appliances such as refrigerators the load is more evenly distributed during the day and night.

In reality the load curve varies depending on several factors other than the appliances used. The shape of the load curve smoothens out with an increasing number of households, as the chance of every household using their peak demand at the same time for example is reduced [81]. The load curve for some devices, such as fans, may also vary with seasons and climate conditions. Hence it may be preferable to manually specify a load curve if possible within the scope of a study in order to increase the reliability of the hybrid system modeling. If such load curves cannot be found in literature there are examples of load curve estimation based on questionnaires or field measurements of electrified villages [82],[83]. In this thesis estimated load curves corresponding to the five levels of the World Bank's Energy Tiers Framework [3] are used for sizing the hybrid systems (Figure 4).

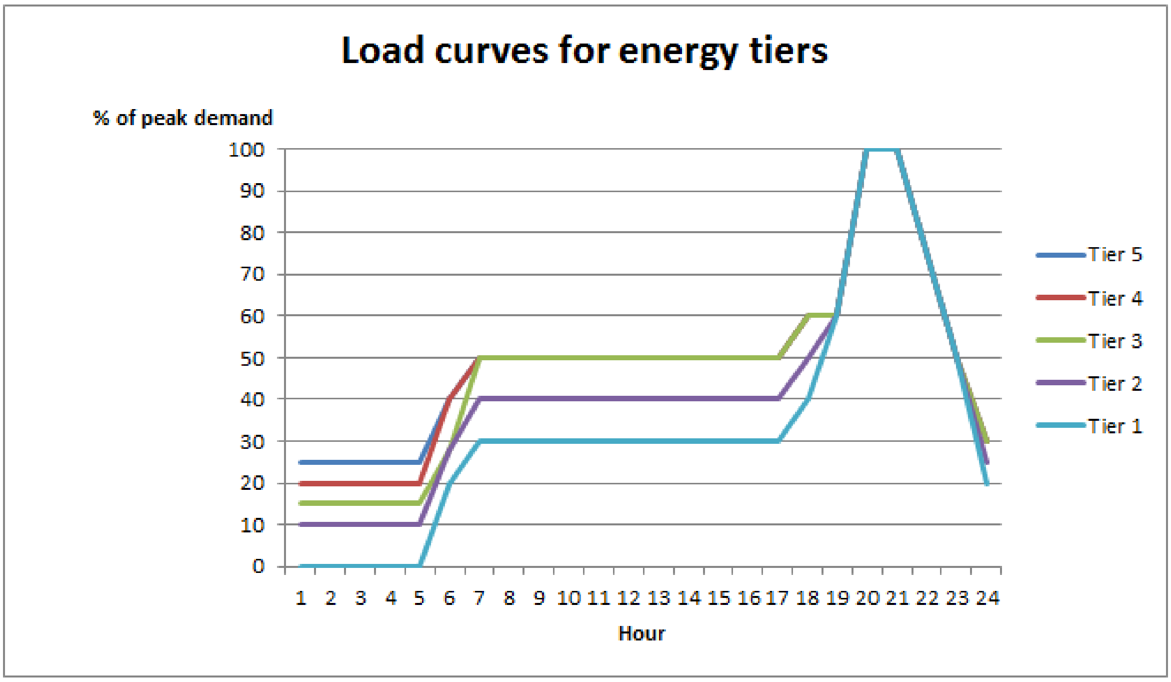

Figure 4. Estimated daily load curves for different household energy tiers, adapted from [84]

4.4.2 Diesel generator

The diesel generator is a dispatchable technology, which in combination with the battery can supply the load when the intermittent renewable technologies are insufficient. The efficiency of the diesel generator is highest when operating at its rated power output. Also, when using diesel generators below approximately 40% of rated capacity for long periods of time they suffer from degradation. For this reason it may be preferable to use multiple generators of different sizes to meet a varying demand. An IEA report states that this may be feasible for diesel systems larger than 50 kW [3]. The efficiency η_G (kWh/l) of the diesel generator can be described as:

$$\eta_G = \frac{P_G}{B_G * P_{NG} + A_G * P_G} \quad (3)$$

Where P_{NG} (kW) is the rated power of the diesel generator, P_G (kW) is the power output and A_G (l/kWh) and B_G (l/kWh) are consumption coefficients. The coefficients can be approximated by A_G=0.246 and B_G=0.08145 [85]. Based on these coefficients the efficiencies while operating between 10 and 100% of the rated power of a diesel generator can be seen in Figure 5.

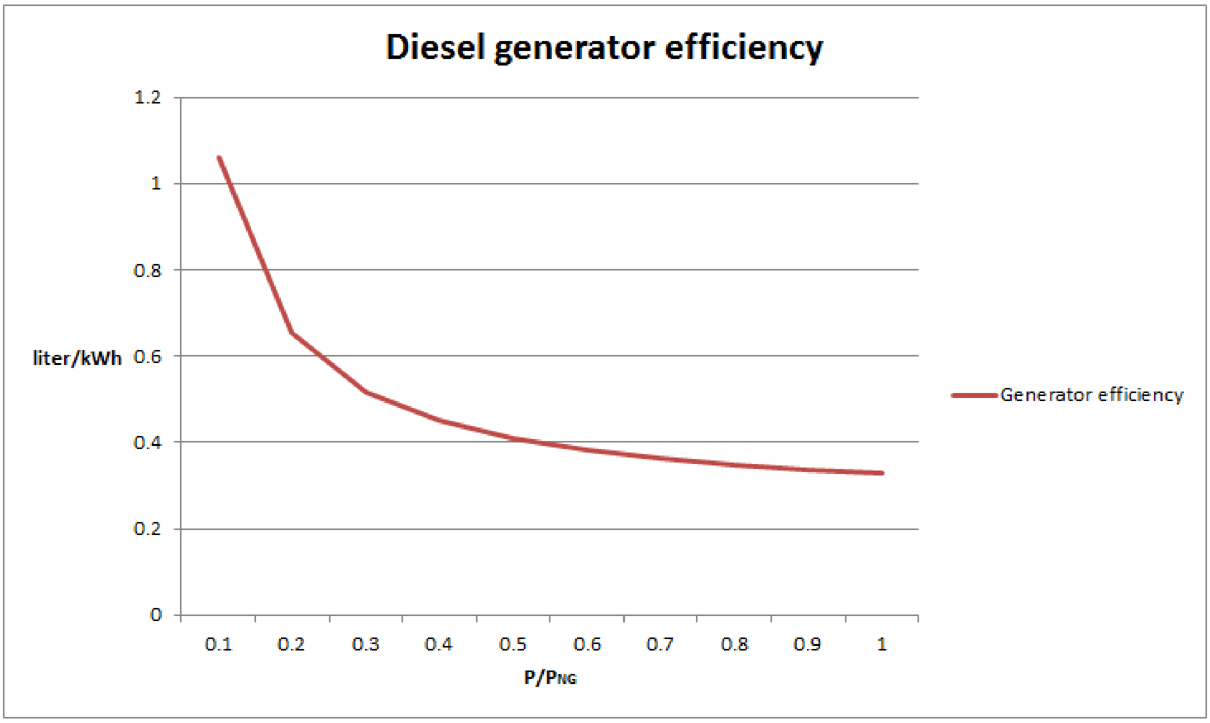

Figure 5. Diesel generator fuel efficiency compared to power output

4.4.3 Battery

Lead-acid batteries are often used for off-grid energy storage due to a combination of technological and economic factors. The efficiency of these batteries, defined as the output power relative to the input power is estimated to be approximately 85% [86]. The lifetime of the batteries depends both on the number of charge-discharge cycles as well as the depth of discharge (DOD) of each cycle. With higher DOD the lifetime of the battery is significantly reduced, and it is preferable to keep the state of charge (SOC) above some minimum level in order to prevent irreversible chemical damage. This minimum level is somewhat ambiguous, but a value around 40% [87], [88] is common in the literature. Based on [87] the state of charge during charging hours can be described in a simple manner by:

$$SOC_t = SOC_{t-1} * (1 - \sigma) + (E_{GEN} - \frac{E_L}{\eta_{INV}}) * \frac{\eta_{CHARGE}}{C_{BATTERY}} \quad (4)$$

Where σ is the self-discharge rate, E_{GEN} (kWh) is the energy generated by the PV panels and the diesel generator, E_L (kWh) is the demand load, η_{INV} is the inverter efficiency, $C_{BATTERY}$ (kWh) is the battery storage capacity and η_{CHARGE} is the battery charging efficiency. Similarly the SOC during the discharging process can be described by:

$$SOC_t = SOC_{t-1} * (1 - \sigma) + (\frac{E_L}{\eta_{INV}} - E_{GEN}) * \frac{\eta_{DISCHARGE}}{C_{BATTERY}} \quad (5)$$

Where $\eta_{DISCHARGE}$ is the discharge efficiency of the battery. The self-discharge rate can be approximated as 0.02% per hour [87].

The battery life is calculated using an Ah throughput model. This means that the battery is assumed to be able to cycle through a certain amount of energy (described as Ah or Wh) before it needs to be replaced. In the simplest form of the Ah throughput model this amount can be decided by the battery capacity and average cycle DOD according to Equation 6 [89]:

$$E_{THROUGHPUT} = C_{BATTERY} * DOD * C_F \quad (6)$$

Where $E_{THROUGHHUT}$ (kWh) is the total energy that can be cycled through the battery before battery failure and C_F is the cycles to failure, which depends on the average DOD. For e.g. 60% DOD the value of C_F is approximately 950 cycles. Hence, the battery life can be estimated by dividing $E_{THROUGHPUT}$ by the energy that is cycled through the battery in one year.

4.4.4 Photovoltaic panels

The output power P_{PV} of PV panels can be described by Equation 7 [90], [91]:

$$P_{PV} = P_{RATED} * f_{PV} * \frac{G_t}{G_{STC}} * (1 - \alpha_P * (T_t - T_{STC})) \quad (7)$$

Where P_{PV} (kW) is the power output during the time-step, P_{RATED} (kW) is the power output at Standard Test Conditions (STC), f_{PV} is the PV derating factor, G_t is the GHI (kWh/m^2) during the time-step, G_{STC} (kWh/m^2) is the GHI at STC, α_p is the temperature coefficient of power, T_t (K) is the temperature during the time-step and T_{STC} (K) is the temperature at STC. The derating factor over 20 years is estimated to be 90% [92].

4.4.5 Wind turbine

The wind turbine has been modeled in a simple manner describing the output by use of the power curve. The power curve of a Vestas V-42 600 kW turbine has been used for this purpose (Figure 6) [93]. The turbine has a cut-in speed of 4 m/s below which the turbine generates no power, and a cut-off speed of 25 m/s above which no power is generated either. Using the average wind speed during the hour the corresponding power output from the wind turbine can be determined from the power curve.

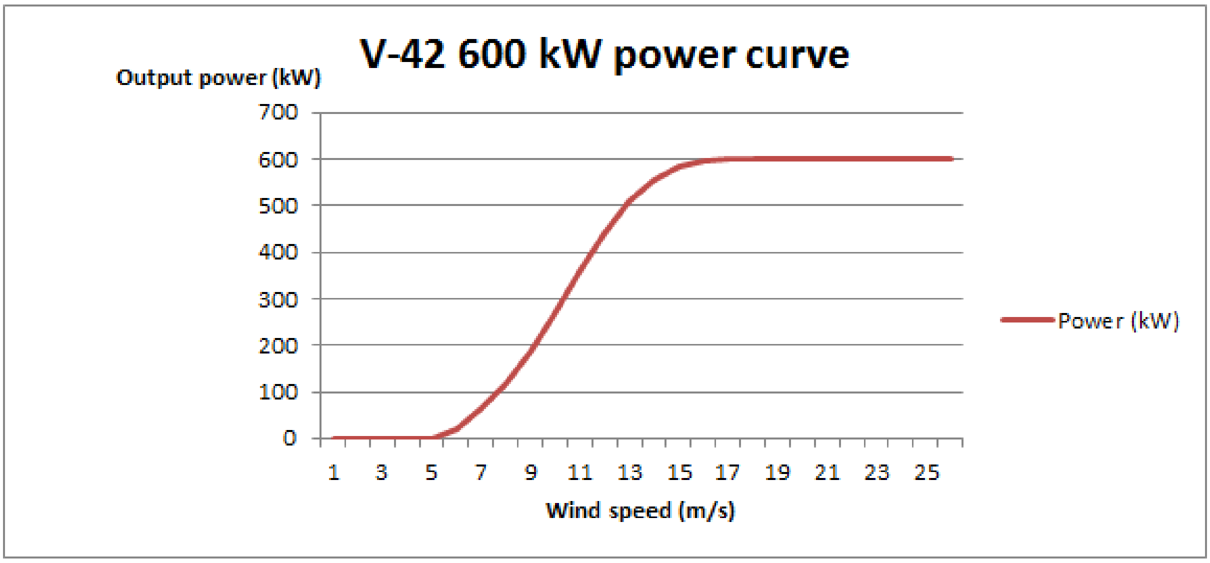

Figure 6. Power curve of Vestas V-42 based on [88]

4.4.6 Control system and inverters

The load and the different components of the HES are based on either AC or DC current. In order to convert between AC and DC a bi-directional inverter is considered. The bi-directional inverter functions as both an inverter (which converts AC to DC) and a rectifier (which converts DC to AC). As in [85] the bi-directional inverter is sized to have the same power output as the maximum load of the system if the system contains both AC and DC components. The inverter efficiency is estimated at 92%.

4.4.7 Energy resources

The cost and availability of energy resources varies spatially. As described in Chapter 2 the cost of diesel increases based on the travel time to large cities. This is defined as cities with a population above 50 000 people in this thesis. The renewable resource availability depends on location and temporal variations. There are several available GIS datasets that give average annual values of e.g. solar GHI or wind speed for countries, regions or globally. However, obtaining hourly values which may be necessary for hybrid system modeling for every location may be both more challenging and time-consuming. An alternative approach is to synthesize hourly data based on average values, which is described for GHI and wind speed below.

4.4.7.1 Global Horizontal Radiation

The incident global horizontal radiation depends on both the movements and rotation of the earth relative to the sun, as well as clouds and other factors. In order to run the simulation hourly GHI values are required for every hour. The GHI varies both during the day, but also with the seasons. Hourly values for one location in central Tanzania for one year have been retrieved from Solar Radiation Data [94] for the purpose of this study. The solar resource varies spatially as well. The hourly values have been scaled using Equation 8:

$$GHI_t = GHI_{t,SoDa} * \frac{GHI_{YEAR}}{GHI_{YEAR,\ SoDa}} \quad (8)$$

Where GHI_t (kWh/m^2) is the global horizontal irradiation in the hour, $GHI_{t,SoDa}$ (kWh/m^2) is the GHI in the hour from the SoDa data, GHI_{YEAR} (kWh/m^2) is the total annual GHI in the cell and $GHI_{YEAR,SoDa}$ (kWh/m^2) is the total annual GHI of the SoDa data.

This way the relative annual and daily variations are maintained, but scaled to sum up to the annual GHI in each cell. The difference in required PV capacity for Tier 5 in a PV-battery system using the above method with scaled values or from SoDa for three locations can be seen in Figure 7. As can be seen the difference stemming from downloading data from different locations may be considerable, especially for lower annual GHI. The difference in LCOE for PV-hybrid systems may be mitigated as a different hybrid configuration relying on more or less diesel generation depending on the solar resource.

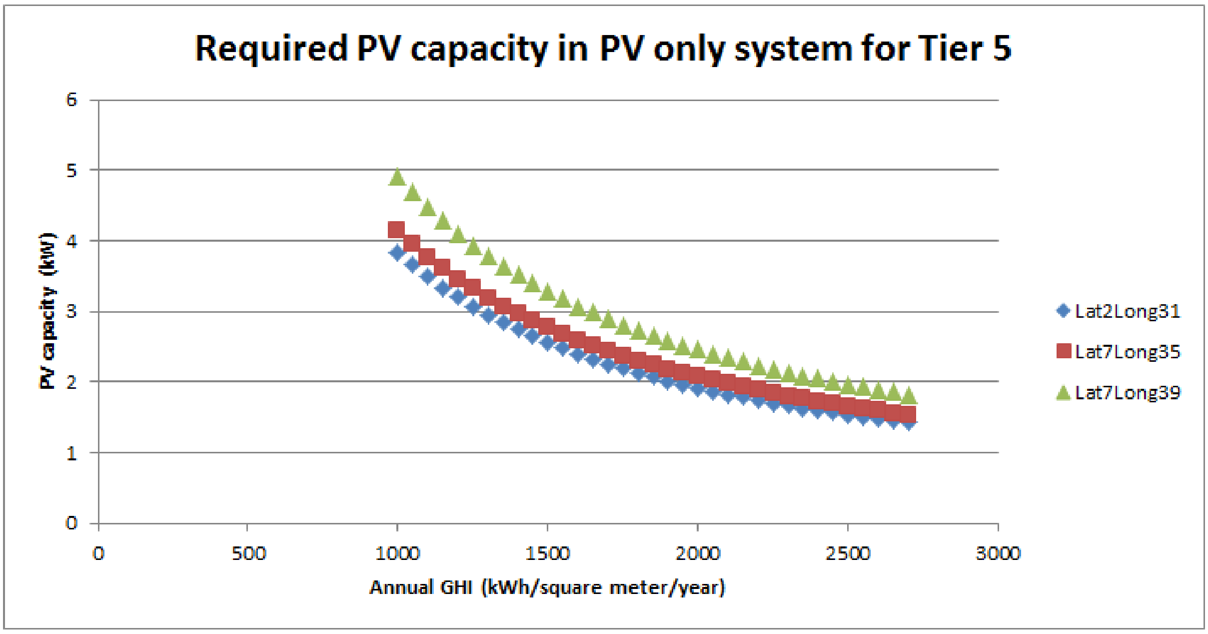

Figure 7. Required PV capacity for Tier 5 using SoDa data from three different locations

4.4.7.2 Wind speed

Similar to the solar resource it is not realistic to collect hourly wind speed data for every grid cell. Instead a method to generate synthesized hourly data based on the monthly average wind speeds and the variations depending on the time of the day has been used. The method was developed by Dufo-López and Bernal-Augustin for use in optimization of stand-alone systems [95]. Equations 9 to 13 below follow the methodology described in their paper. In the first step of the process Weibull numbers from a Weibull distribution are calculated for each hour of the year using:

$$Weibull_{d,h} = \left[-\theta_h^b * \ln(1 - a_{d,h)}\right]^{1/b} \quad (9)$$

Where $a_{d,h}$ is a random number between 0 and 1, and θ_h^b is the Weibull distribution scale factor for each hour of the day of the month, with b form factor:

$$\theta_h = \ w_{m,h} \ /\Gamma(1 + \frac{1}{b}) \ (10)$$

Where Γ is the Gamma function and $w_{m,h}$ (m/s) is the average wind speed in the month at that hour. In the second step correlated values for every hour of the year, c_h, are calculated using:

$$c_{d,h} = Weibull_{d,h}, \qquad if\ d = 0\ and\ h = 0 \quad (11)$$

$$c_{d,h} = \ c_{d,h-1} * f_c + Weibull_{d,h} * (1 - f_c) \ \ otherwise \quad (12)$$

Where f_c is the correlation coefficient. In the next step a part of the value is subtracted using:

$$e_{d,h} = c_{d,h} - f_{SUBTRACT} * w_{av,m} \quad (13)$$

Where $f_{SUBTRACT}$ is the subtraction coefficient and $w_{av,m}$ (m/s) is the average wind speed in the month. If the resulting value is negative the result is converted to zero. Finally for each month the $e_{d,h}$ values are summed and a correction factor is calculated and multiplied in order to have the generated wind speeds have the same average as the desired monthly average.

The calculations are performed for a number of distribution values b and subtraction values $f_{SUBTRACT}$ and compared to match a target distribution, b_{DIST}. The values b and $f_{SUBTRACT}$ that generates wind speeds that best matches the target distribution are chosen. In this thesis the target shape parameter b_{DIST} has been set equal to 2, as is common in wind energy simulations.

Hourly time-series are generated for each integer value of average annual wind speed from 5 m/s up until the maximum wind speed encountered in the GIS wind speed dataset. At average wind speeds below 5 m/s wind turbines are not considered a viable alternative. The relative monthly and hourly variations have been retrieved from DTU Global Wind Atlas, which has this information available for free for any region in the world.

The performance of the synthetization method has been examined by comparing the annual output from a 600 kW turbine using both hourly wind speed data from SoDa and generated data for the corresponding annual average wind speeds for three locations. The SoDa wind speeds are measured at 10m height above the ground. The hourly wind speeds have been extrapolated to a hub height of 50 m using Equations 14 [96], and the synthesized data has been generated using the annual average extrapolated wind speed:

$$U_Z = U_{Z,REF} * \left(\frac{z}{z_{REF}}\right)^{\alpha} \quad (14)$$

Where U_Z (m/s) is the wind speed at hub height z (m), $U_{Z,REF}$ (m/s) is the wind speed at the reference measurement height, z (m) is the hub height and z_{REF} (m) is the reference measurement height. α is the dimensionless power law coefficient given by [96]:

$$\alpha = 0.37 - \frac{0.088 * \ln(U_{REF})}{1 - 0.088 * \ln\left(\frac{Z_{REF}}{10}\right)} \quad (15)$$

The average annual measurement wind speed at location A, B and C is 5.5, 4.3 and 3.7 m/s respectively. When extrapolated to 50 m this corresponds to 7.7, 6.2 and 5.6 m/s. As can be seen in Figure 8 - 10 the synthesized data have a higher frequency of wind speed above 15 m/s, as well as wind speeds close to zero. Figure 11 also displays that the synthesized data leads to a higher annual energy generation. The results also seem to indicate that this phenomenon is more pronounced at lower average wind speeds.

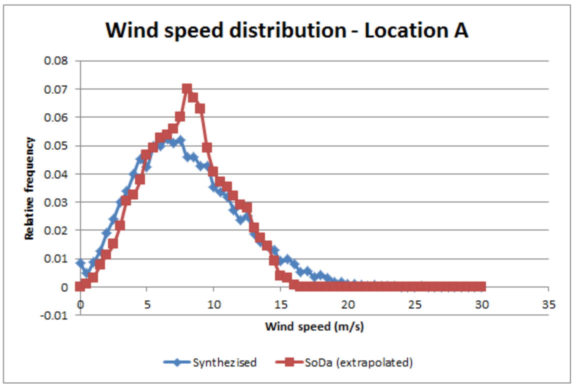

Figure 8. Wind speed distribution in location A

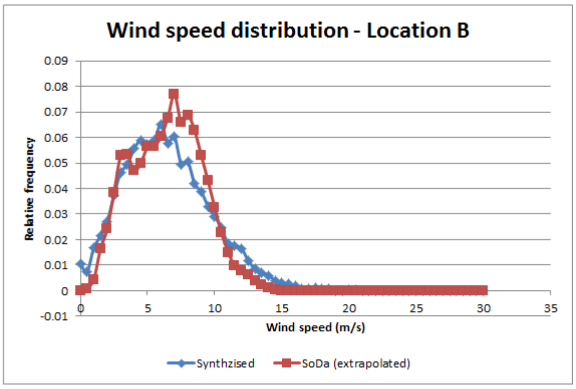

Figure 9. Wind speed distribution in location B

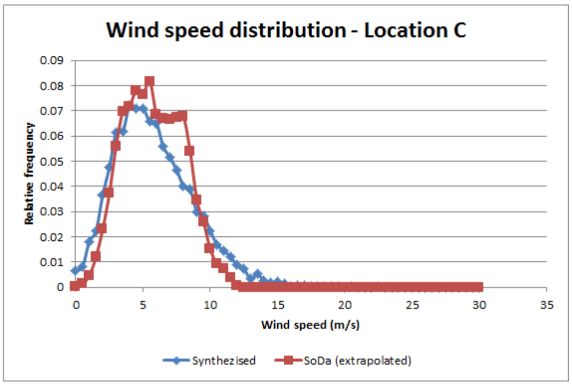

Figure 10. Wind speed distribution in location C

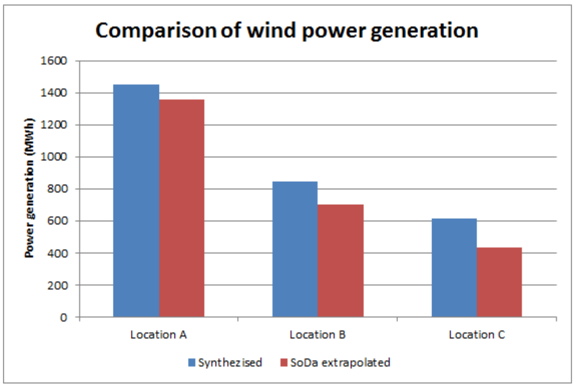

Figure 11. Annual energy generation

4.5 Modeling of PV-diesel system

The proposed PV-diesel HES can be seen in Figure 12. In order to reduce power transformation losses the whole system in the PV-diesel-configuration is considered to be working with DC, i.e. the load is DC and a DC diesel generator is considered. Both the PV panels and battery deliver DC by default.

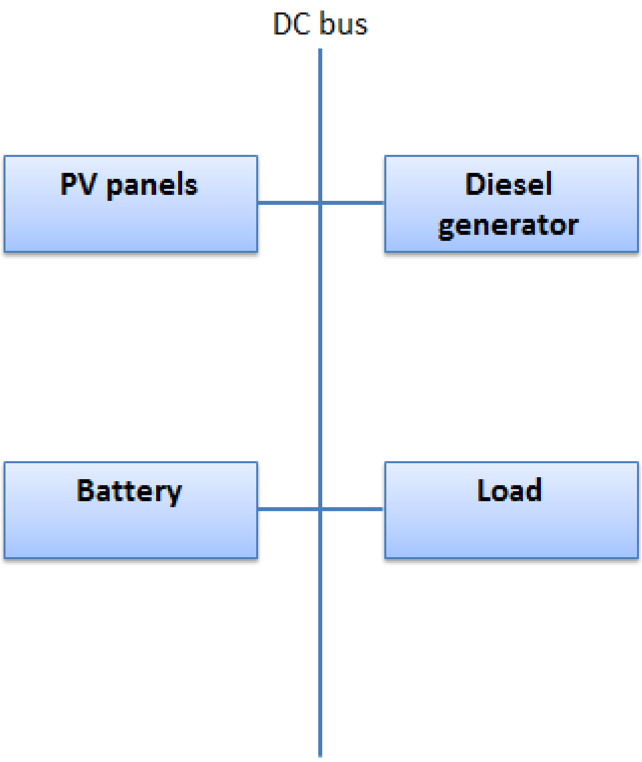

Figure 12. PV-diesel scheme for HES

The dispatch strategy used in the proposed model takes into account system reliability and aforementioned limitations of the technologies. In the first step the non-dispatchable PV generation is determined. The net load is then calculated, defined as the energy demand minus the PV generation per hour. If the net load is negative, i.e. if PV generation is larger than demand, the excess energy is stored in the battery. Else the net load is met by a combination of diesel generators and battery discharge, depending on the time of day and a few other conditions. Several combinations of dispatch strategies have been tested, and the one which generated the lowest LCOE in most cases is described below.

- During night hours, between 00-06 a.m., the demand is usually low and the diesel generator should be turned off to prevent it from operating at low capacities and to prevent noise. This means that during the night the batteries are dispatched primarily. The diesel generator is used only if the batteries are unable to meet the load. If the diesel generator is dispatched it runs at its rated capacity to charge the batteries if there is excess energy, in order to limit the time it is used during the night.

- During the morning and midday the batteries are dispatched primarily to meet the net load. If the batteries are insufficient the diesel generator is dispatched to meet the load. During this time of day the diesel generator operates at the lowest capacity needed to meet the demand, subject to a minimum level of 40% of the rated capacity as described above. The reason for not charging the batteries with the diesel generator is that around mid-day are the hours with the best conditions for the PV panels, and thus charging the batteries using the diesel generator may lead to possible excess energy generated by the PV panels to be wasted while more diesel fuel is consumed instead.
- During the late afternoon and evening hours when the demand peaks the diesel generator is dispatched primarily. During these hours the diesel generator is run at the maximum capacity required to meet the load and charge the batteries, so that they can be used during the night. The battery is discharged only if the net load cannot be supplied by the diesel generator alone.

In the first round of calculations the PV size required to meet the demand is calculated for a battery size corresponding to two day’s full demand, with no diesel generator considered. The unmet demand by the system is determined and the PV panel size is altered until the unmet demand is less than a specified percentage of the annual energy target. Typical values in the literature for this factor range from 0 to 5% [97]-[99]. For this thesis the condition was set to 5% maximum, but may be altered by the user in future studies. When the condition is met the panel size is stored. This maximum unmet demand is within the reliability requirements for Tier 4, but is higher than the reliability requirements for Tier 5.

In the second round a number of combinations of battery and panel sizes are considered in combination with diesel generators. Also, combinations without a battery are considered. The size of the diesel generator required to meet the demand for each configuration of batteries and PV cells is calculated using an iterative process starting at 0 kW and increasing stepwise until the unmet demand is less than 5% as described above. The resulting diesel capacity, PV capacity, battery size, fuel use and battery wear is stored for each configuration.

Using the results from the second round a two-dimensional reference table for LCOE depending on the annual GHI and diesel cost divided into specified intervals is created. For each combination of GHI and diesel cost the LCOE of all the system configurations considered is calculated using the stored results and the component costs and specifications, and the lowest one is chosen. Finally this LCOE is compared with the other technologies included in OnSSET for choosing the least-cost technology configuration in the cell.

4.6 Modeling of wind-diesel system

Figure 13 shows the configuration of the wind-diesel system. In order to best utilize the wind energy and limit conversion losses both the load and the diesel generator based on AC in this hybrid system.

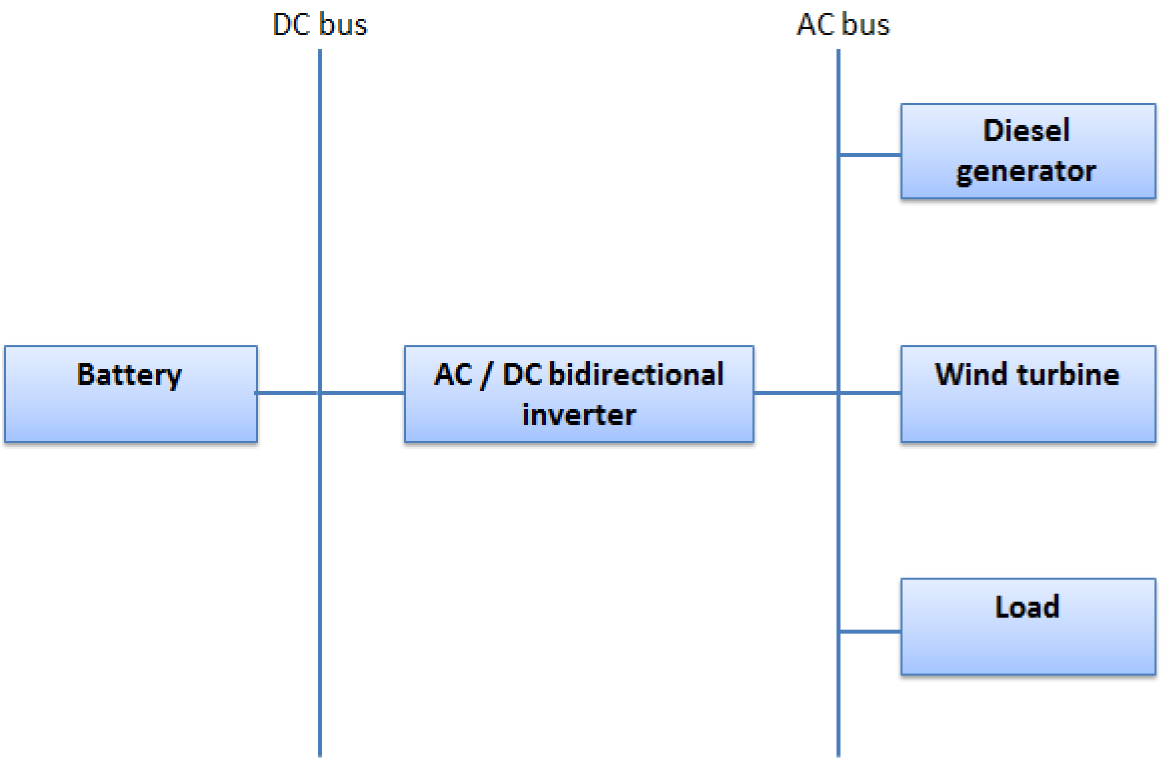

Figure 13. Configuration of the wind-diesel system

The wind resource does not display such a strong daily pattern as the solar resource. There are some statistical trends regarding which are the windiest and least windy hours during the day when averaging over long time-spans. However, the wind speeds are very stochastic and these long-term patterns are not considered for the dispatch strategy. For the wind-diesel system only one dispatch strategy is used during the whole day.

The wind resource is non-dispatchable by nature and the net load is defined as the load minus the wind generation in the hour as in the previous hybrid system. At negative net loads the excess energy is again used to charge the batteries. The battery is dispatched primarily to meet the load in order to limit diesel consumption. If the stored energy is insufficient or the batteries are at a low SOC the diesel generator is run at full capacity instead to supply the net load and charge the batteries using the excess energy, if any.

The model is run in a similar fashion as the PV-diesel hybrid. In the first step the required wind turbine capacity to generate as much energy as the demand in one year is calculated for reference. In the second step a number of both smaller and larger wind turbines are considered together with combinations of batteries and diesel generators. For each combination that successfully meets the maximum unmet demand target the capacities and battery wear are stored and used as input for the LCOE calculations.

A reference table for wind-diesel hybrid systems is created. For each combination of diesel cost and average annual wind speed at a specified interval step the least-cost system configuration is decided and the LCOE and investment costs are stored. In each cell in the OnSSET code the corresponding LCOE from the reference table is compared to the other technologies to choose the most affordable one.

5 Tanzania case study

The new additions to OnSSET have been implemented in a case study of Tanzania. The results with the new additions have been compared and contrasted to those of the original code. The first sections of this chapter describe the country and its energy status, followed by a description of the OnSSET study and the results.

5.1 Country overview

Tanzania is located in eastern Africa, bound by the Indian Ocean in the east, Kenya and Uganda in the north, Mozambique, Malawi and Zambia in the south and DR Congo, Burundi and Rwanda in the west. The country covers 947 000 square kilometers and is home to roughly 52 million people. A majority of the population is younger than 25 years of age, and the country experiences a population growth rate of approximately 3% per year [100].

The GDP per capita is merely 879 USD as of 2015. This places the nation on the 161st place in the world, below the sub-Saharan average of 1594 USD/capita. In 2011 76.1% of the population lived below the poverty line, and 46.6% in extreme poverty[9] [101]. A majority of the population works in the agricultural sector. However, the natural resources and tourism sectors have driven the economy to a growth rate around 6-7% in recent years which is a fast growth compared to the African average [102].

5.2 Current electrification status

Currently 36% of the population in Tanzania has access to different levels of electricity services. Approximately two thirds of the electrified population is connected to the grid, while the rest use electricity generated from off-grid technologies. The use of electricity is not evenly distributed amongst the population as only 11% of the rural population has access to electricity services. The government is currently working towards expanding the electrical grid with the goal of reaching 75% connectivity by 2033 [103].

5.3 Power sector status

Generation of electricity in Tanzania has been heavily dependent on hydropower in the past. This dependency has decreased as large reserves of natural gas have been found and are being used for electricity generation. Currently the electricity is generated by an almost even split of hydropower, natural gas and liquid fuels for a combined total of 1583 MW generation capacity. 45% of the electricity generated is used by the residential sector (see Figure 14). Tanzania also currently imports electricity from Zambia, Kenya and Uganda. The country envisions at least 10 000 MW of generation capacity by 2025 to meet the demands of a growing population [104]. The transmission network infrastructure is aged and the system suffers from large technical losses

[9] Poverty and extreme poverty here defined as 3.1 and 1.9 USD/day in 2011 PPP respectively

[103]. The total transmission and distribution losses in the system have fallen from 25% in 2010 to 17% in 2016 due to a relatively large decrease mainly in the distribution losses [105], [106].

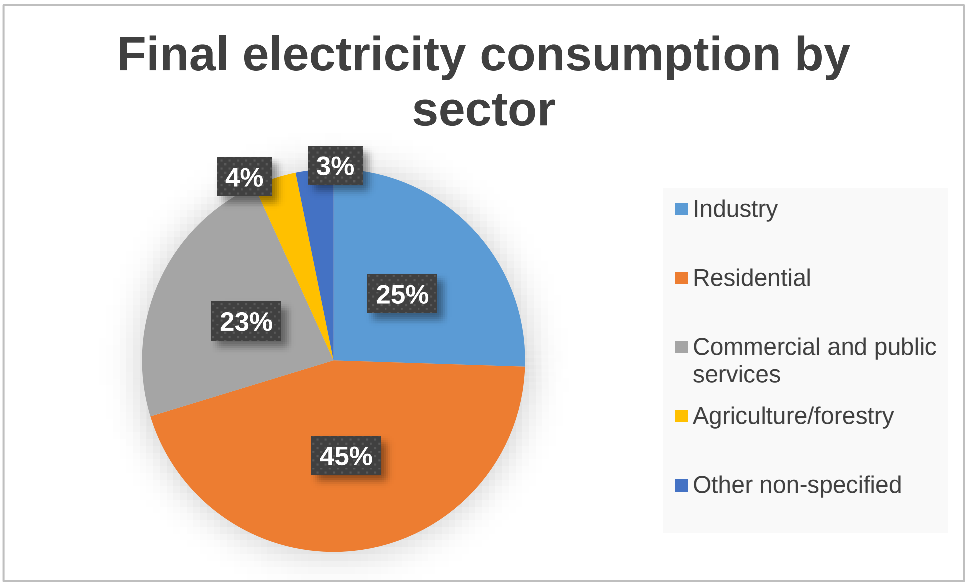

Figure 14. Final electricity consumption by sector [107]

The major electricity supplier in Tanzania is the Tanzania Electric Supply Company Limited (TANESCO). TANESCO is owned by the government of Tanzania and its activities involve transmission, distribution and sale of electricity. The company was established in its current form in 1964 following a merger of Tanganyika Electricity Supply Company and Dar es Salaam Electricity Supply Company [104]. TANESCO is currently dealing with large amounts of debts. A majority of these debts stem from 2011 when TANESCO was forced to invest in costly emergency power plants due to increases in the electricity demand in combination with a drought that hampered the country's hydro potential.

5.4 Energy policies and incentives

The first national energy policy (NEP) for Tanzania was presented in 1992. The purpose of this policy was to ensure an efficient practice within the energy sector. Since then two new NEPs have been presented in order to replace the one from 1992; one in 2003 and the latest one in 2015. The NEP of 2003 resulted in, amongst other things, a large increase in installed capacity and an increase in the electricity consumption levels per capita. With this policy the country also managed to more than double the population connected to the grid. NEP of 2015 aims at implementing incentives for a larger participation from private actors in the energy sector. With the sustainable energy for all initiative in mind the new policy also focuses on improving energy conservation, energy efficiency and increasing the diversity within the energy mix. For the electricity sector in particular the aim of the policy is to increase the rural electrification rate and enhancing the reliability of the transmission and distribution network [108]. In the Power System

Master Plan (PSMP) of 2012 it has been proposed to further diversify the electricity mix to include natural gas, coal, hydro, renewable and nuclear energy. In the plan it is mentioned that the country requires 3 400 additional MW to be installed during the period of 2013-2017 and close to 9 000 MW by 2035. The investment cost required for this is calculated to be just below 41 billion USD. In the long-term plan to 2035 the installed capacity was proposed to be divided as in Figure 15 [106].

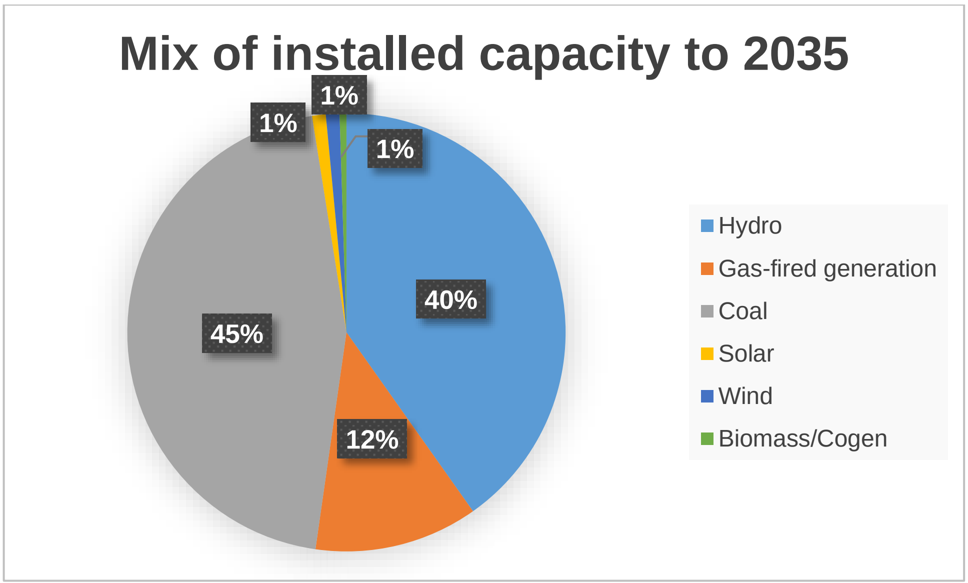

Figure 15. Mix of installed capacity to 2035 according to base case scenario in PSMP 2012 [106]

5.5 OnSSET study

In order to generate a model with OnSSET, various socio-economic and technological parameters need to be specified. These parameters describe various characteristics in the country such as demographics, technology costs and grid characteristics. Additionally a number of GIS datasets are required. A description of the input parameters and GIS datasets can be found in Appendix A.

5.5.1 Discount rate

The discount rate is an important factor in the analysis of energy systems. In the energy sector the costs that are typically discounted are the variable costs and the fixed operation and maintenance (O&M) costs. These costs tend to be higher for non-renewable technologies and therefore a high discount rate has a negative effect on the competitiveness of renewable technologies such as Wind and PV systems. As an example of the importance of discount rate a study found that the discount rate on PV systems had a larger influence on the feasibility than GHI [109]. Hirth and Steckel showed in their analysis that as the discount rate increases the largest increase in LCOE can be seen for wind power while coal and gas plants have a smaller increase [110].

In Tanzania the official interest rate of the Bank of Tanzania is considered as the discount rate. The discount rate has changed considerably during the last 45 years. The highest value recorded during the period was 68% and the lowest was 4%. Currently the interest rate is at 12% [111].

Due to the fluctuating nature of the discount rate it might be useful to conduct a sensitivity analysis in order to examine the effect that the discount rate has on the technology mix. To highlight the importance of the discount rate both 12 and 8% have been examined in the study.

5.6 Implementation of new modules in OnSSET

The energy demand relationships from Chapter 3 and hybrid systems from Chapter 4 have been incorporated into OnSSET. Below follows a description of how they have been implemented and the effect that has on the method of running analysis.

5.6.1 New demand method

Some of the findings from Chapter 3 have been implemented as a new method for determining the energy demand. In the original code one energy target for urban and one energy target for rural areas may be specified by the user. In the new method an iterative process is proposed which determines the energy tier depending on GDP and the expected electricity price as calculated by OnSSET using Equation 16 based on the relationship found in Chapter 3:

$$\log(electricity/household/year) = -0.9266 * \log(electricity\ price) + 0.4793 * \log(GDP) \quad (16)$$

Where the electricity is measured in kWh/household/year, the electricity price in USD/kWh and the GDP in USD/km^2. The GDP is based on a GIS dataset and projected to 2030 using an expected GDP growth rate. The LCOE calculated by OnSSET is considered as the electricity price.

The methodology for the new energy demand assessment can be seen in Figure 16. There are four steps in the methodology and they are as follows:

1. Energy target in each cell is calculated using the grid electricity price and the projected GDP. The grid electricity price is used as it is the lowest LCOE that can potentially be achieved in each cell, thus giving the highest level of energy consumption and as follows also the highest added benefit.
2. Least-cost electrification technology and corresponding LCOE in every cell is generated using OnSSET.
3. New expected annual energy consumption is calculated using the LCOE as electricity price and the GDP in the cell.
4. Energy demand is reclassified as an energy tier between one and five.

Step 2-4 are repeated using the energy tier for each cell calculated in step 4 as energy target in step 2. When the energy tier in a cell is changed other technologies may be the most affordable choice in the cell and the LCOE changes correspondingly. The process is repeated until the tiers are not changed anymore.

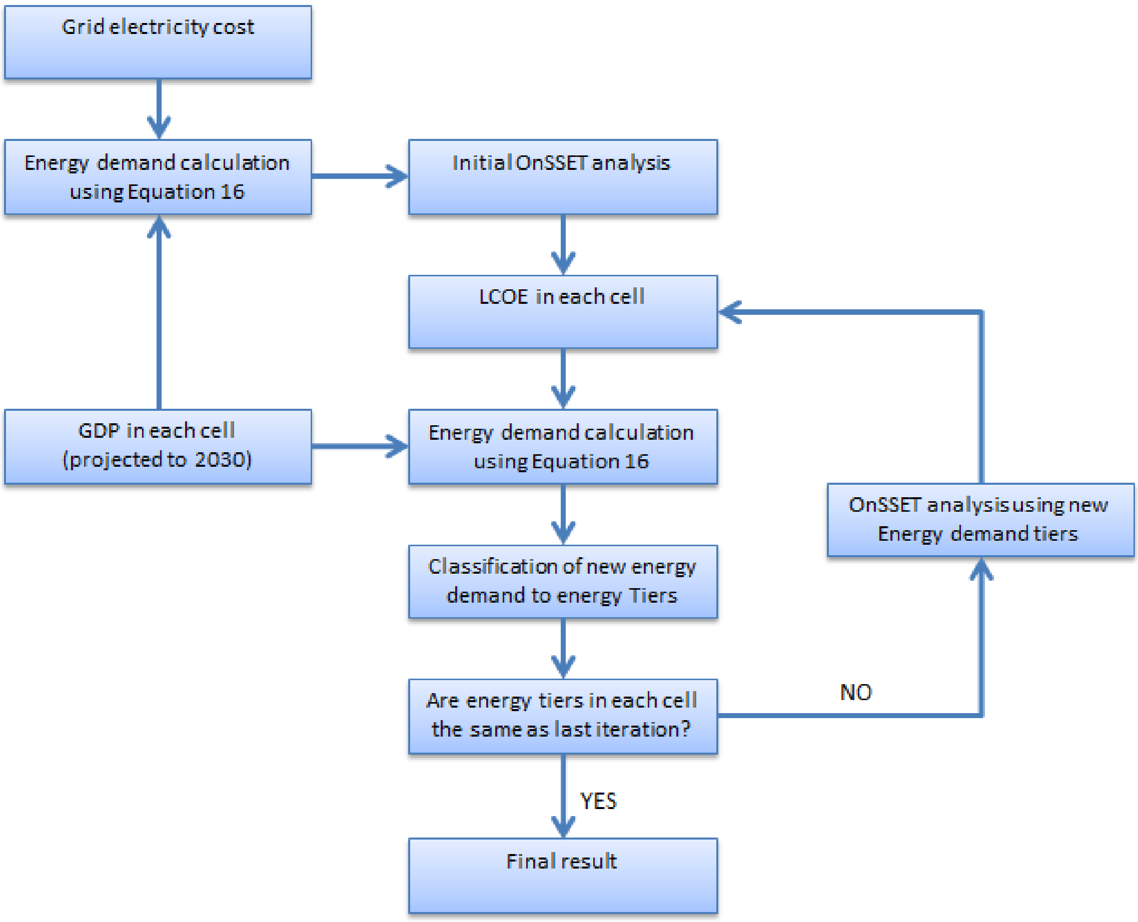

Figure 16. Process of the new demand methodology

5.6.2 Hybrid systems

The two hybrid systems have been added to the list with the seven already existing technology configurations. In each cell the LCOE for the hybrid systems is retrieved from the two reference tables that have been generated, using the diesel cost and solar/wind resource in the cell for indexing. Both hybrid systems are considered MG systems. Therefore the cost of the transmission and distribution (T&D) system is also calculated depending on the energy target and the population in the cell as for the other MG technologies. The LCOE of the T&D system is calculated and added to that of the components to give the total LCOE of each hybrid system in the cell. Finally the LCOE of all nine technology configurations are compared to determine the least-cost electrification option.

5.7 Tanzania case study results

The results of the case study are presented for three methods. The first is a standard OnSSET study for the five energy tiers, using the original seven technology configurations. In the second method, the demand is calculated based on GDP and electricity price as described in the previous section. The third method is identical to the first except for the inclusion of the two new hybrid system technologies. All results are presented for two discount rates, 8% and 12%, as this is one of the most important input parameters affecting the LCOE and technology choice as described above.

5.7.1 Standard OnSSET results

Figure 17 displays the results for the least-cost technology population shares, i.e. the share of the population that would be electrified by each technology by 2030. The results are presented for all five tiers and two discount rates for each tier. Grid connection would be the most utilized technology in the majority of the scenarios. For Tier 1, Tier 2, and Tier 3 mostly standalone off-grid technologies are utilized where grid-connection is not favorable. For Tier 4 and Tier 5 this shifts towards MG technologies. It can also be seen that higher discount rates lead to more diesel-based technologies, while lower discount rates lead to a higher share of renewable technologies.

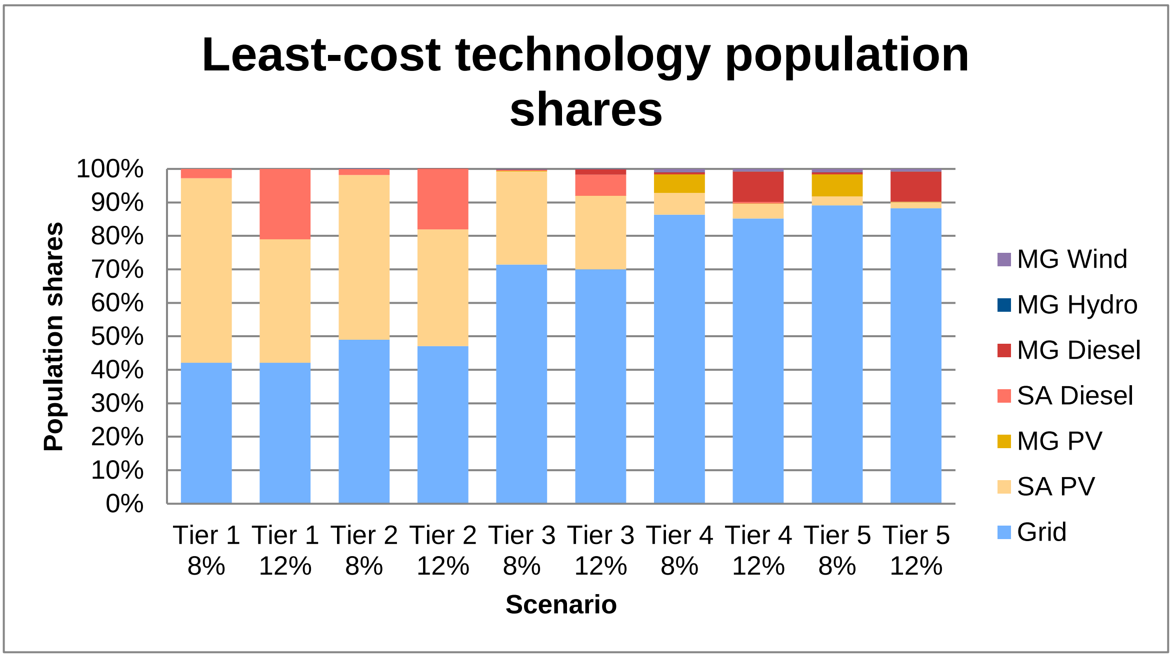

Figure 17. Share of population using each technology for different tiers and discount rates

Figure 18 shows two maps of the least-cost technology configuration distribution for Tier 3 with 8 and 12% discount rate. In both cases the spread of grid-connection and MGs occur where there are high population densities. For higher energy tiers the extent where grid- and MG technologies are most affordable is increased, while the opposite occurs for lower energy tiers. It can also be seen that many areas where standalone PV or grid-connection is favorable at 8% discount rate are replaced by diesel technologies at 12% discount rate.

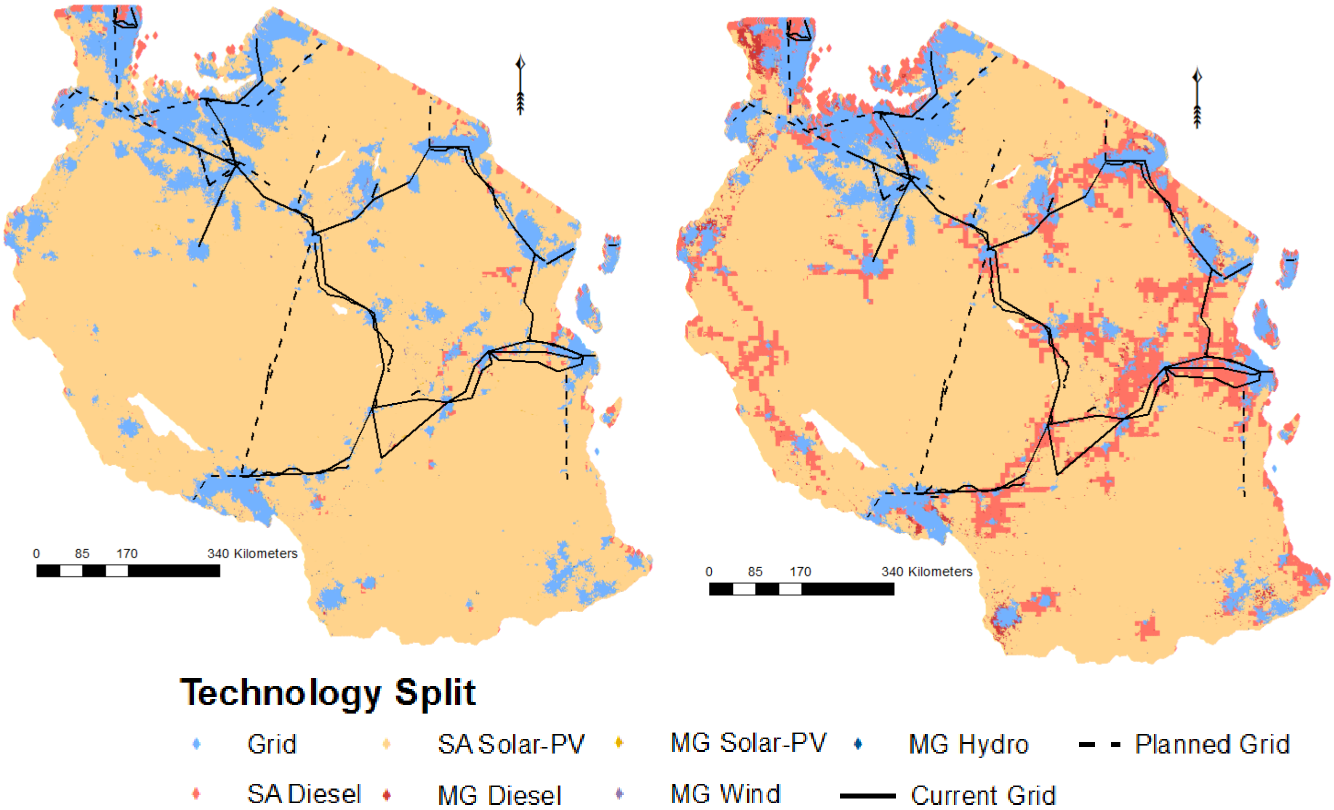

Figure 18. Left: Technology split at Tier 3 and 8% discount rate. Right: Technology split at tier 3 and 12 discount rate

As the electricity demand increases with higher tiers, the amount of power generation capacity increases (Figure 19). The largest power generation capacity installments are required in new power plants connected to the national grid for all scenarios. Standalone PV would need approximately as much added capacity as grid-connected power plants for Tier 3. The scenarios with the high discount rate require slightly lower installed capacities as diesel technologies which have higher capacity factors replace renewable technologies.

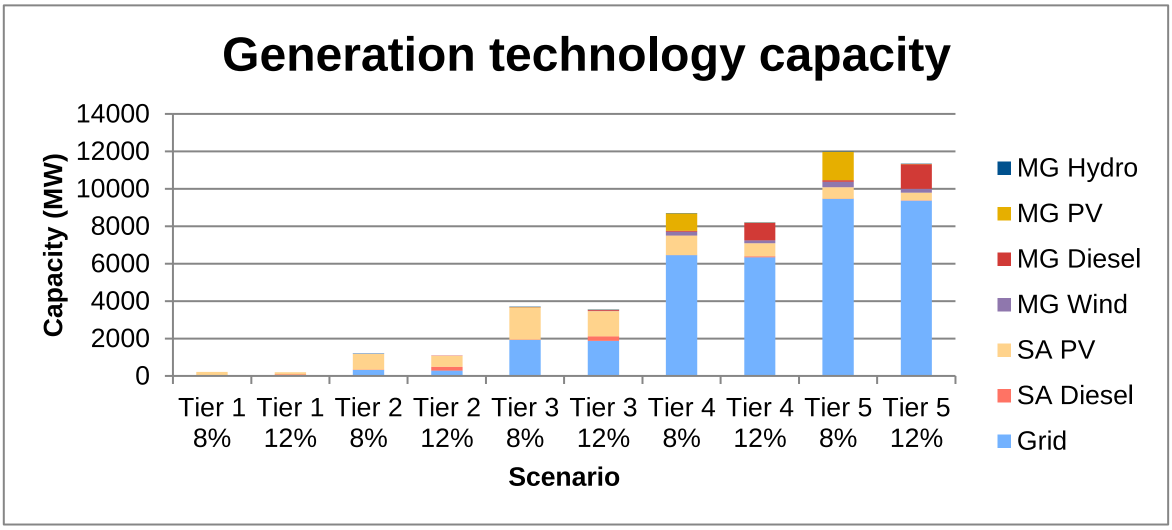

Figure 19. Capacity installed for different tiers and discount rates

As for the capacity requirements the investment costs also increase with power demand for higher tiers (Figure 20). Providing Tier 1 level of electricity consumption in all of Tanzania would require investments of 3 billion USD, and reaching Tier 3 would require 24 or 22 billion USD at 8 or 12% discount rate respectively. Achieving the highest energy targets in all of Tanzania would require investment costs of 47 or 55 billion USD at 8 or 12% discount rate respectively. This is close to the 41 billion USD investments identified in the PSMP. It should be noted that the scenarios with higher discount rates and greater use of diesel technologies require lower capacity investment cost than scenarios which rely more on renewable technologies.

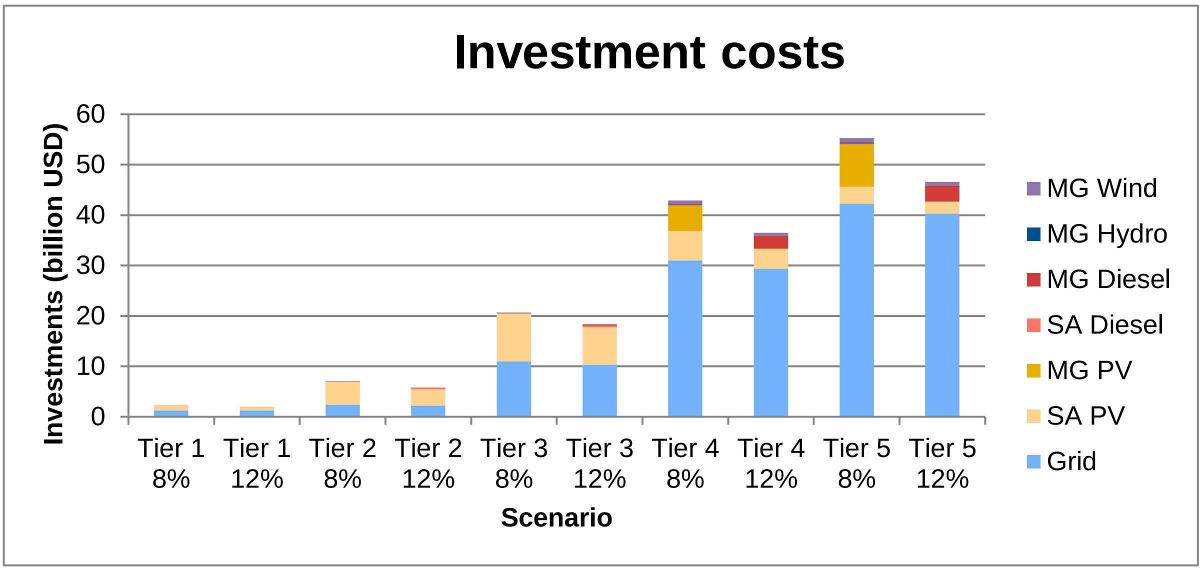

Figure 20. Investment costs for different scenarios

5.7.2 New demand method results

Using the new demand assessment method it was found that most of the population in Tanzania could afford to reach somewhere between Tier 1 and Tier 3 electricity consumption by 2030. The GDP growth was assumed to be uniform throughout the whole country and remain at 7% until 2030 as has been the case in the last years. Figure 21 displays the share of the population for each tier generated by the new demand method. Notably the results are identical within one tenth of a percent for the two different discount rates even though the LCOE is affected by the discount rate.

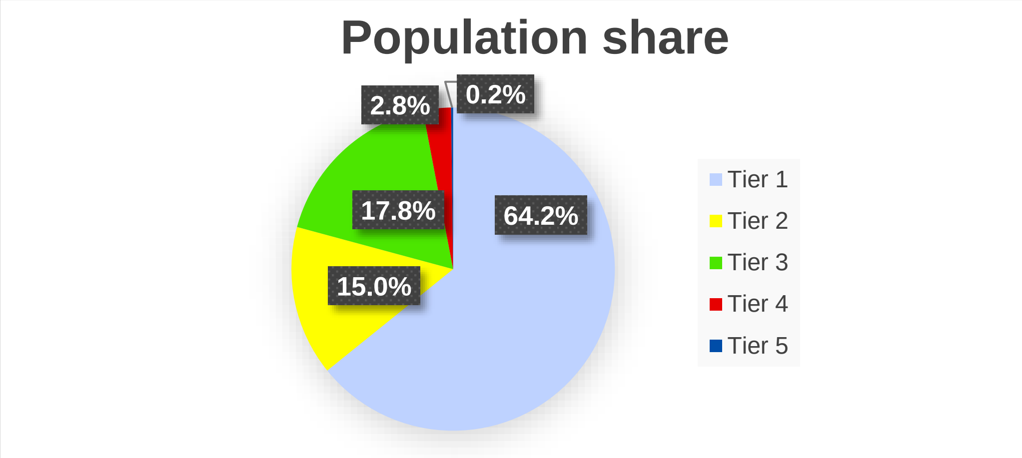

Figure 21. Population share in each electrification tier

The total investment cost required amounted to 3.6 and 3.3 billion USD for a discount rate of 8 and 12% respectively. This sum is between what is required for Tier 1 and Tier 2 energy targets for the whole country in the original results. The majority of the costs are allocated for capacity investments for generation, transmission and distribution using the national grid, followed by standalone PV capacity. Standalone diesel investments make up only a marginal part of the investments in both cases (Figure 22). This corresponds to capacity installments of 660 MW of grid-connected plants and 171 MW standalone systems at 8% discount rate and 659 MW of grid-connected plants and 149 MW standalone systems at 12% discount rate. The investment costs are reduced slightly for the higher discount rate as some standalone PV systems are replaced by diesel standalone systems.

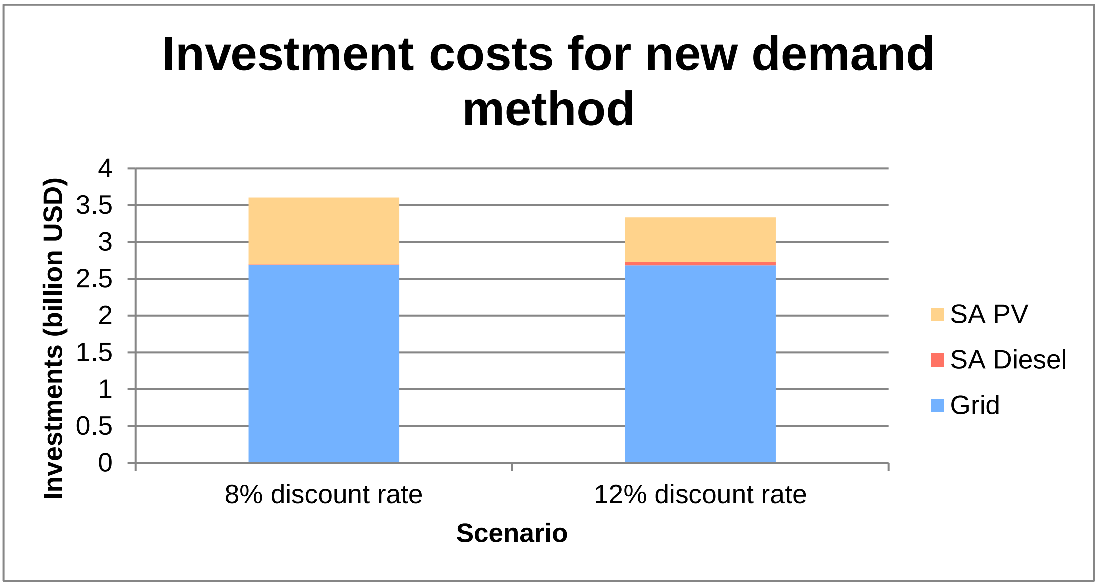

Figure 22. Investment costs for 8 and 12 % discount rate

Only three technologies were utilized using this method; grid-connection, standalone PV and standalone diesel (Figure 23). The higher energy tiers are encountered around the cities in

Tanzania (Figure 24). Especially around Dar es Salaam, Arusha and Mwanza which are the three largest cities. In rural areas the expected energy consumption is lower. The areas where grid-connection was the chosen technology were also the areas where the energy consumption could be expected to be higher.

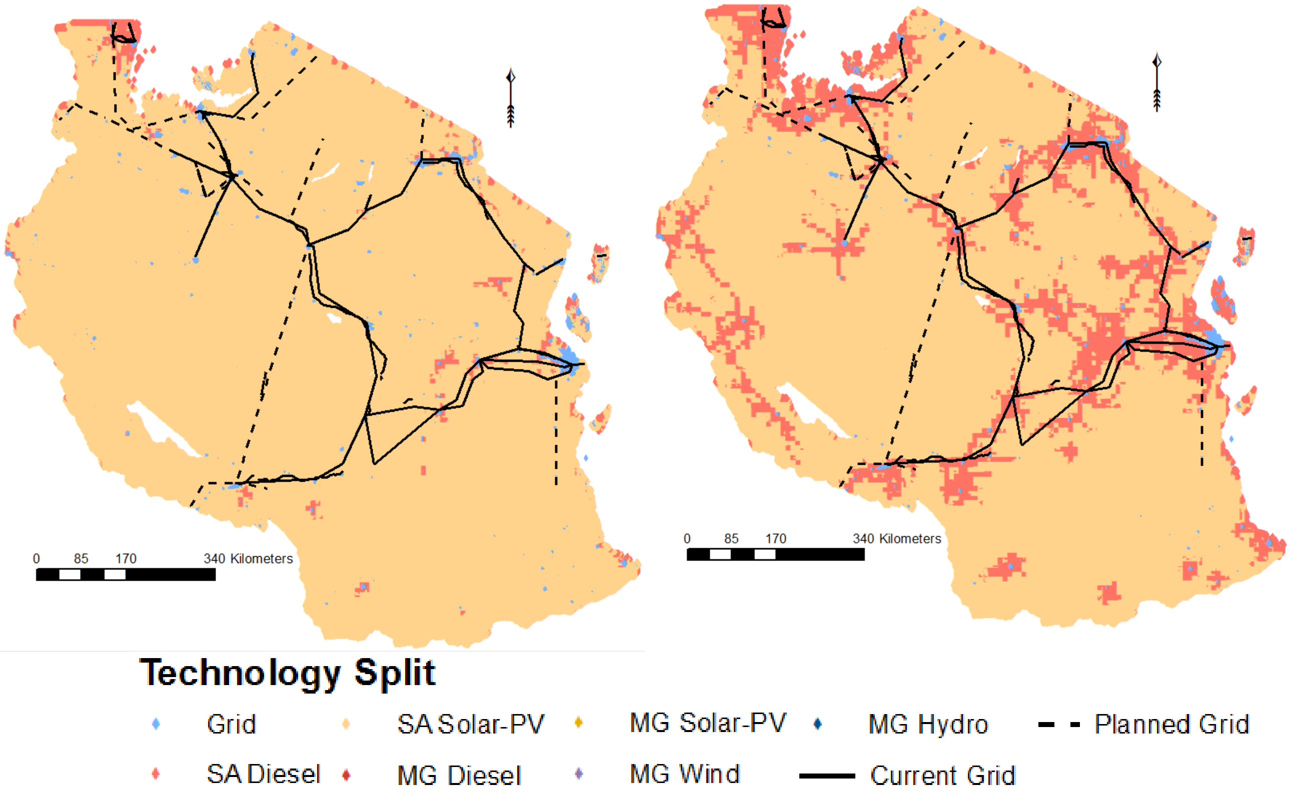

Figure 23. Left: New Demand method technology split 8% discount rate in 2030. Right: New Demand method technology split 12% discount rate in 2030

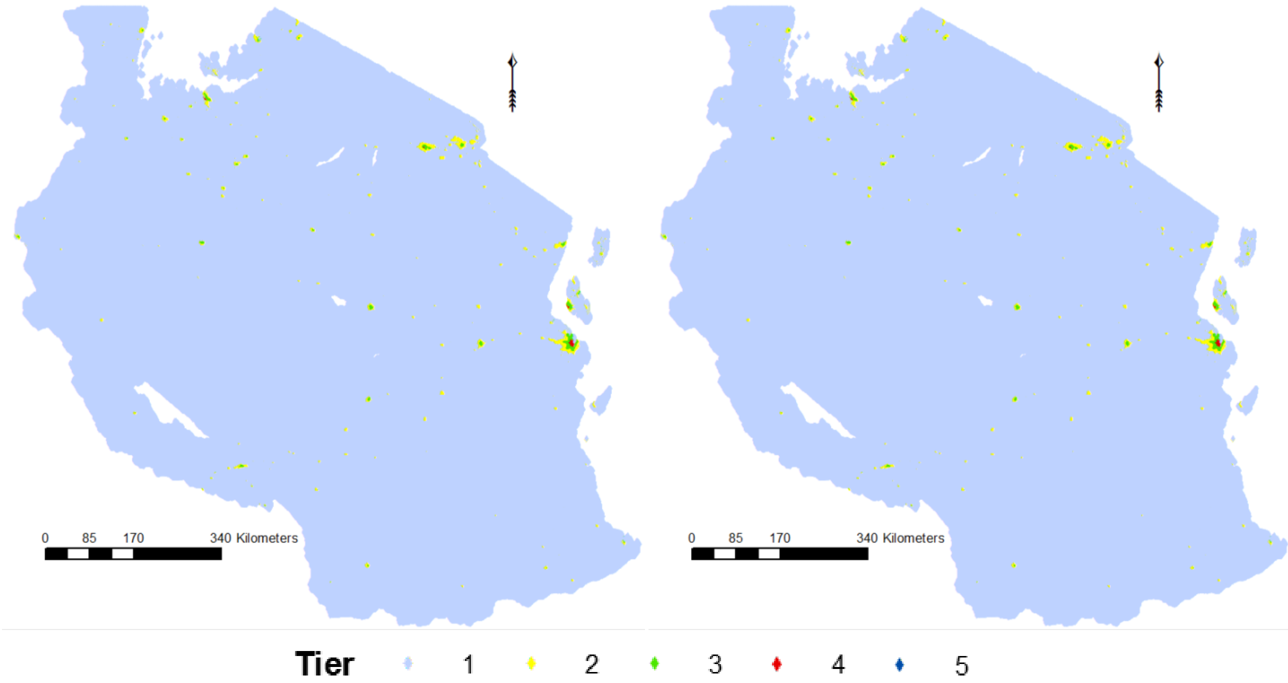

Figure 24. Left: Tier-split in New Demand method at 8% discount rate in 2030. Right: Tier-split in New Demand method at 12% discount rate in 2030

5.7.3 Hybrid systems result

The hybrid systems impact on the technology choice has been considered for Tier 3 and Tier 5 energy targets, and the two discount rates. At Tier 3 the share of hybrid systems is less than 1%. At Tier 5 the share of hybrid systems is 1.5% and 1.2% at 8% and 12% discount rate respectively. The shares of other technologies are very similar to the results without hybrid systems, where grid-connection is the technology with the highest share.

Both hybrid systems considered are MG systems, and therefore inherit the same attributes as the other MG technologies. I.e. they need a sufficiently high population density to justify the cost of the transmission and distribution system compared to the standalone technologies. They are also more costly than the national grid, which often delivers electricity at the lowest LCOE if the extension and connection costs can be economically justified. Figure 25 shows the LCOE of PV-diesel hybrid compared to the least-cost technology of the other four MG technology configurations in each cell. It can be seen that the LCOE of PV-diesel hybrid systems are within -5% to 10% of the least cost (non-hybrid) MG technology configurations in most of Tanzania at both Tier 5 and 12% discount rate as well as Tier 3 and 8% discount rate. When the same comparison is performed for wind-diesel hybrids (Figure 26) the LCOE is within 0-10% only in a very small area, and are 20-50% more costly in some areas. In the majority of the country however the proposed wind-diesel hybrid systems are even more costly, or not considered at all due to low wind speeds.

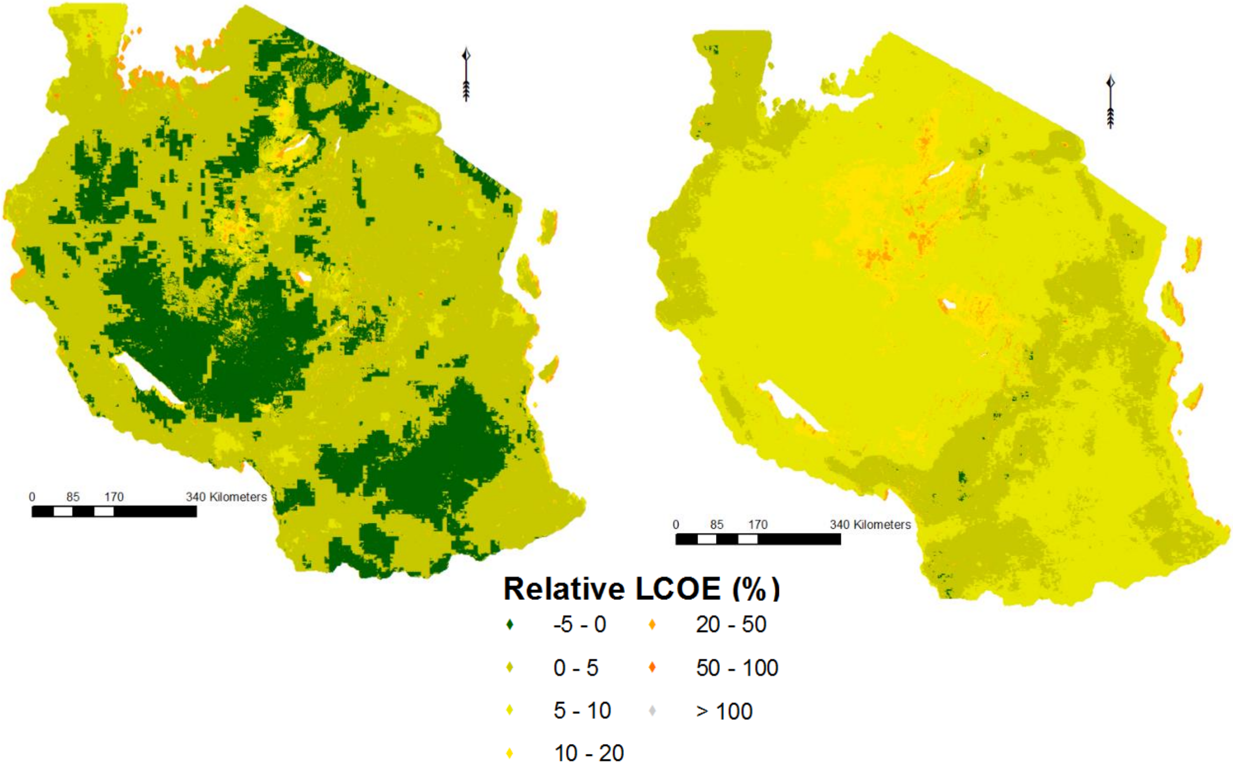

Figure 25. Left: PV-diesel relative LCOE. Tier 5, 12% discount rate. Right PV-diesel relative LCOE. Tier 3, 8% discount rate

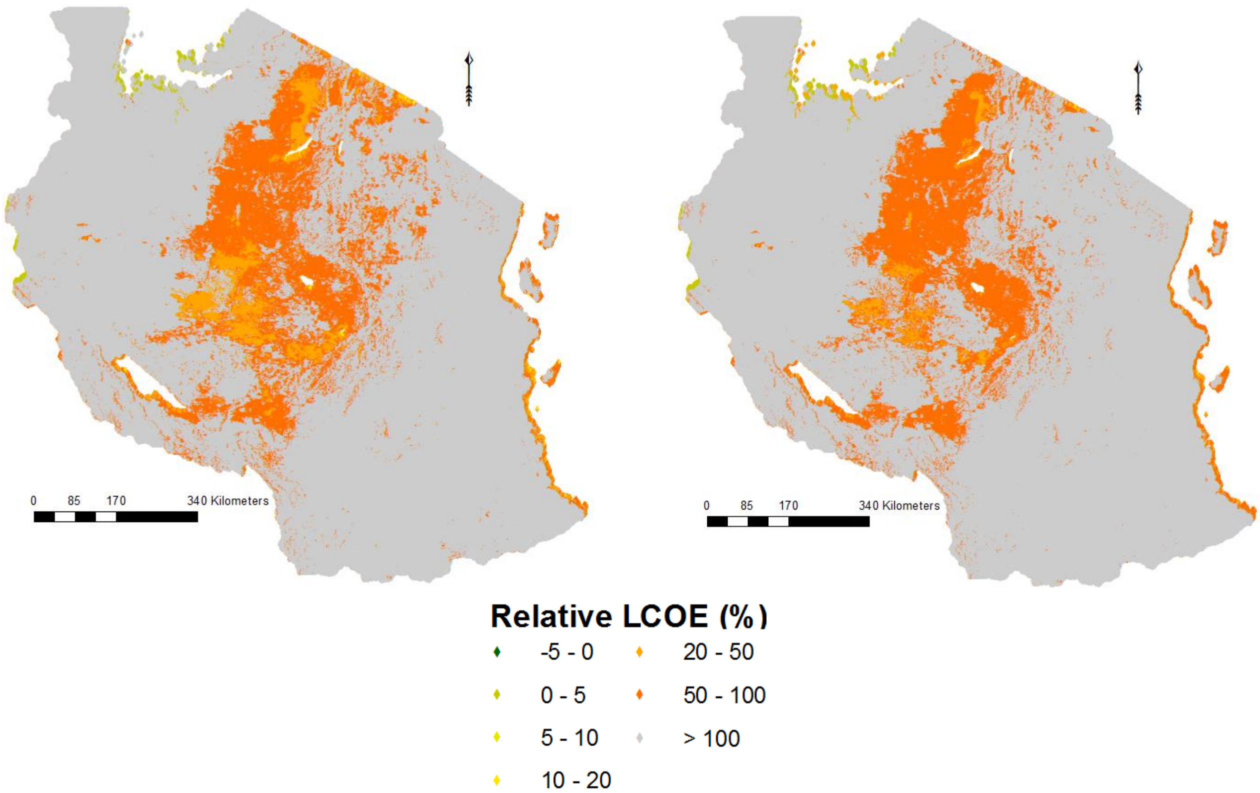

Figure 26. Left: Wind-diesel relative LCOE. Tier 5, 12% discount. Right: Wind-diesel relative LCOE. Tier 3, 8% discount

6 Discussion

6.1 Case study Tanzania

The results of the case study of Tanzania using the original OnSSET method showed that grid-connection is likely an important factor for increased electrification rates in Tanzania, especially in densely populated areas. However, off-grid systems would also have an important role in all scenarios. This is especially true for the three low levels of electricity access, but even for levels corresponding to Tier 4 and 5 12-15% of the population would benefit from off-grid technologies.

The discount rate was found to have the expected effect on the results. At lower discount rates PV systems were the most affordable option in most areas where grid-extension was not economically justifiable. At higher discount rates however the share of diesel technologies increased due to their low investment cost and high O&M cost which is discounted. PV systems still made up the majority share of the off-grid technologies for the three lower tiers where standalone systems were preferable to mini-grids as the large investment costs of these systems were still more affordable than the fuel costs associated with diesel in the long term.

The capacity requirements for the three lowest tiers are significantly lower than what can be found in the plans of the government. Tier 4 is also below the 9 000 or 10 000 MW in the plans, but considering the fact that only the residential electricity consumption is considered in this report Tier 4 may be quite high compared to those plans. When comparing to the electricity generation mix by 2035 as stated in the PSMP it can also be noted that solar PV systems play a larger role in the OnSSET results. The other technologies are more difficult to compare as they depend on the electricity mix in for national grid electricity in OnSSET.

6.2 Geo-spatial demand assessment

The correlation between GDP, electricity price and electricity consumption was used in the New Demand method for the case study of Tanzania. With this new approach the results showed that in most of the country an electricity access target in the range of Tier 1, 2 and 3 seems plausible while Tier 4 and 5 are likely only in some small areas of the largest cities. In other urban areas Tier 3 and Tier 4 seem likely to a large extent. This is seemingly a logical mix of tiers in the country as it can be expected that urban areas are more likely to achieve higher levels of electricity access. The technology split changed in the same manner as it did without the new methodology applied with SA diesel being more prominent as the discount rate increased which is in line with what the literature stated.

The amount of people in each tier stayed practically the same with the two different discount rates. This is a rather interesting result as the LCOE changes when the discount rate is altered. The tiers were however affected by the technology choice and subsequently the LCOE in each cell, since multiple iterations were required. However the almost non-existent change due to the impact of the discount rate may indicate that the GDP has a larger impact than the LCOE for determining the energy tier using Equation 16.

Furthermore, it is important to note that the relationship used for the New Demand method in this paper may be country-specific. It needs to be examined whether the coefficients in Equation 16 are universal or if similar correlations can be calculated for each country. Since the LCOE is derived from OnSSET and the GDP map has a global extent the data requirements for the new demand method are met for other countries as well.

Finally a strong correlation between variables does not necessarily mean that changes of the independent variable necessarily cause the changes in a dependent variable. In order to ensure this, the causality needs to be examined. A limitation of the geospatial electricity demand assessment is the fact that the causality has not been studied. One additional limitation is that since the exact household locations have not been available the studied variables have been altered so that they give a representation of the wards.

6.3 Hybrid energy systems

The two hybrid energy systems did not significantly change the electrification mix results in this study. For higher electrification tiers, where mini-grids were competitive or advantageous compared to standalone systems they had a small impact. The potential impact at these scenarios was limited since grid-connection was used for the vast majority of the population.

PV-diesel hybrid systems were economically competitive with the other mini-grid systems. This means that a higher level of energy reliability might be achieved at lower or slightly higher costs as the other mini-grids with these systems. In other countries where grid-connection can be expected to be economic for a smaller share of the population at the higher energy tiers PV-diesel systems may play a more important role. The PV-diesel hybrid energy systems required relatively large investment costs, and as for PV only systems they were found to be more competitive at lower discount rates.

The wind-diesel systems proposed on the other hand were significantly more costly than the other mini-grid technology configurations. There might be other system configurations or dispatch strategies that can lower the cost of these systems, but at this point it seems unlikely that they will be cost-competitive with the other technologies in OnSSET using the current model.

The added benefits that may come from HES compared to systems relying on a single fuel are not reflected when the technologies are chosen based on LCOE, which is a purely economic tool. Further developments of the OnSSET tool may include a system to include more factors in the technology choice such as system reliability and also environmental effects such as CO_2 emissions. These factors may affect the adoptability of the systems and the environmental sustainability. By adding these options a wider variety of analyses using OnSSET may be possible. If such a multi-criteria choice is included it seems possible that mini-grid may prove to be more important than in the current analysis.

In future studies it could be of interest to further examine how the shape of the daily load curves affect the results of the model. Demand side management strategies such as peak load shavings may play an important role in decreasing the overall cost to reach universal electricity access. The five daily load shapes used in this thesis reflect a general case depending on the appliances which can be used at the respective tier. The load curve could also be improved when looking at a specific location, but the five load curves provides a good approximation for this model. The remaining off-grid technology configurations currently do not consider how the daily load shape varies for different energy targets. Including such information for these technology configurations as well may affect the results of the model and such developments of the model should also be examined.

As with any model there are uncertainties associated with the modeling of the hybrid systems. A very important aspect is the modeling of the renewable energy resources in every cell. Using average country patterns as for the wind speeds or randomly selected data as for the GHI means that the model will likely provide too optimistic results in some areas and too pessimistic results in others. Still the model may provide locations where hybrid mini-grid potential exists, which can then be further examined using local weather data.

7 Conclusions

In order to increase global electricity access the use of energy models integrated with GIS may be beneficial during the planning process. The OnSSET study of Tanzania showed that a combination of grid-connection and off-grid technologies can provide the least costly electrification strategy at costs close to or below what the government has identified in the Power System Master Plan. Grid power and PV systems were found to be the most important technologies in order to bring the electrification rate to 100% by 2030.

Some new additions to the OnSSET methodology were developed. It was found that combinations of GDP, electricity price and NTL could describe household electricity demand well. The usefulness of NTL is dubious as there are problems of oversaturation and bottom censoring that need to be overcome in order to reach the full potential of NTL for remote sensing of residential electricity demand. Furthermore an alternative method to the currently uniform electricity access targets was proposed which allowed to differentiate the electricity access targets based on GDP and electricity cost. This method may provide a new option for the OnSSET analysis, but further research is needed to determine the universality of the correlation on which it is based. It may also be preferable to further investigate the direction of the causality of the correlation.

Additional developments of the OnSSET methodology were introduced by addition of two hybrid technologies to the list of electricity generation options which may be more reliable than off-grid generation based on a single fuel. PV-diesel mini-grids were found to be competitive economically with the other mini-grid technologies, while wind-diesel mini-grids were more costly. Some new data-requirements were introduced in order to include these systems, mainly for the synthetization of weather data. It was also proposed that a new technology decision system which includes more aspects than LCOE may allow for a wider variety of analyses, in which HES are also likely to be more competitive.

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Appendix A

The various parameters included in OnSSET are presented in Table A-1, followed by the GIS datasets used in Table A-2. The grid capacity investment costs and grid electricity price are results of a study that utilizes OSeMOSYS [112]. OSeMOSYS is a tool that describes the least cost power generation mix based on the net present value.

Table A-1. OnSSET input parameters

Socio-economic parameters	Value
Population 2015 (million) [105]	51.8
Population 2030 (million) [105]	74
Urban population share 2015 (%) [105]	27
Urban population share 2030 (%) [105]	50
Urban household size (2012) (people/household) [113]	4.2
Rural household size (2012) (people/household) [113]	5.0
Electrification rate 2015 (%)* [103]	36
Target electrification rate 2030 (%)	100
Technology parameters	
Diesel pump price (USD/l) [114]	0.8
Grid electricity cost (USD/kWh) [112]	0.045
Grid capacity investment cost (USD/kW) [112]	1 324
Grid losses (%) [105]	17
Off-grid generation technology costs [115] – [118]	
Stand-alone diesel capital cost (USD/kW)	983
Stand-alone PV capital cost (USD/kW)	5 500
Mini-grid diesel capital cost (USD/kW)	721
Mini-grid PV capital cost (USD/kW)	4 300
Mini-grid wind capital cost (USD/kW)	2 500
Mini-grid hydro capital cost (USD/kW)	5 000

* OnSSET considers only population using the grid for initial calculations. The number used in the program is therefore 24% as described in Chapter 5.

Table A-2. OnSSET input datasets

GIS-datasets	Resolution	Source
Wind-speed	1 km x 1 km	[119]
Population (2010)	100 m x 100 m	[63]
Night-time lights (2012)	1 km x 1 km	[62]
Power lines, generators, masts and power stations (Existing, 2015)	Shapefile	[66]
Elevation (2003)	3 arc-second	[120]
Travel time (2008)	1 km x 1 km	[67]
Global horizontal irradiation (2005)	3,5 -4 km	[119]
Land cover	0,5 km	[121]
Roads	Polylines	[68]